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Full Length Article

# A systematic review of data fusion techniques for optimized structural health monitoring

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ABSTRACT

Advancements in structural health monitoring (SHM) techniques have spiked in the past few decades due to the rapid evolution of novel sensing and data transfer technologies. This development has facilitated the simultaneous recording of a wide range of data, which could contain abundant damage-related features. Concurrently, the age of omnipresent data started with massive amounts of SHM data collected from large-size heterogeneous sensor networks. The abundance of information from diverse sources needs to be aggregated to enable robust decision-making strategies. Data fusion is the process of integrating various data from heterogeneous sources to produce more useful, accurate, and reliable information about system behavior. This paper reviews recent developments in data fusion techniques applied to SHM systems. The theoretical concepts, applications, benefits, and limitations of current methods and challenges in SHM are presented, and future trends in data fusion methods are discussed. Furthermore, a set of criteria is proposed to evaluate contents and information from original and review papers in this field, and a road map is provided discussing possible future work.

## 1. Introduction

Data fusion strategies were initially developed for military purposes but soon gained interest in non-military applications. Data fusion techniques combine information collected from different sources to extract useful information. They also facilitate more accurate and robust inferences than could otherwise be achieved from individual data. Thereby, data fusion enhances decision-making about a system's state [1,2]. This practice is similar to the human brain's operation, where different senses, such as smell, sight, touch, taste, and hearing, are combined to infer the state of the surrounding environment. As such, data fusion methods aim to aggregate data collected from various and, in many cases, diverse sources that present a system's collaborative or competitive characteristics. As such, these methods can be described following Euclid's notion: "The whole is greater than the part".[1] In other words, the fused data (as a whole) is more enriched with information about the system's state than the individual data obtained from different sources (parts) [3,4]. Through data fusion, data is converted into knowledge-based details to assist in making reliable decisions. These characteristics make data fusion strategies attractive for facilitating SHM [5].

Data fusion practices benefit greatly from data source management and data mining applications. Raw data collected from different sensors usually suffer from imperfections such as incompleteness, data conflicts, and data inconsistency [6]. These imperfections make the extracted data in its raw state undesirable and, thus, often unsuitable for decision-making. Hence, devising a hierarchical transformation of collected data can systematically boost the quality of extracted information. Various types of data fusion architectures are reported in the literature [7,8]. Some traditional and conventional data fusion architectures include the Luo and Kay architecture, Joint Directors of Laboratories (JDL), and Dasarathy's architecture which have been thoroughly investigated by Becerra et al. [9], Kolar et al. [10].

Data fusion techniques can be implemented at different levels based on the processing stage at which the fusion occurs. These data integration levels are typically differentiated between low, intermediate, and high levels. Low-level data fusion is aimed at fusing raw data to obtain a unique representation free of unwanted effects [11]. In mid-level fusion, however, some system characteristics are extracted from the raw data to be further fed into the fusion process [12]. The final decision-making on the system's state can be improved by converting these

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[1] Euclid, Elements, Book I, Common Notion 5

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**Nomenclature**

| | |
|---|---|
| SHM | Structural Health Monitoring |
| JDL | Joint Directors of Laboratories |
| D-S | Dempster–Shafer |
| ML | Machine Learning |
| DL | Deep Learning |
| SNR | Signal-to-Noise Ratio |
| WSN | Wireless Sensor Network |
| QoS | Quality of Service |
| ET | Evapotranspiration |
| DPC | Distance Probability Classification |
| AI | Artificial Intelligence |
| MFD | Fundamental Diagram |
| ED | Eddy Current |
| ML | Maximum Likelihood |
| PNN | Probabilistic Neural Network |
| ANN | Artificial Neural Networks |
| RF | Rotation Forest |
| STFT | Short Term Fourier Transform |
| SVM | Support Vector Machine |
| DIC | Digital Image Correlation |
| CMW | Concrete Masonry Walls |
| AE | Acoustic Emission |
| MSE | Modal Strain Energy |
| DNNs | Deep Neural Networks |
| FD | Fractal Dimension |
| IoT | Internet of Things |
| MSIF | Multi-source Information Fusion |
| RST | Rough Set Theory |
| NDE | Non-Destructive Evaluation |
| MMLA | Multi-Modal Learning Analytic |
| EMI | Electromechanical Impedance |
| EOV | Environmental and Operational Variation |
| UAV | Unmanned Aerial Vehicle |
| EKF | Extended Kalman Filtering |
| PCA | Principal Component Analysis |
| DoD | American Department of Defense |
| SVD | Singular Value Decomposition |
| t-SNE | t-Distributed Stochastic Neighbor Embedding |
| VoI | Value of Information |
| CNN | Convolutional Neural Network |
| CCA | Canonical Correlation Analysis |
| SEC | Soft Elastomeric Capacitor |
| MI | Mutual Information |
| AVs | Autonomous Vehicles |
| PBM | Probability-Based Method |
| EBM | Evidence Reasoning Method |
| KBM | Knowledge-Based Method |
| DSS | Door Surround Structure |
| PDI | Probability-based Diagnostic Imaging |
| ME | Maximum Entropy |
| BAYES | Bayesian |
| NA | Neutral Axis |
| GPU | Graphics Processing Unit |
| BPA | Basic Probability Assignment |
| NB | Naive Bayes |
| DB-SCAN | Density-Based Spatial Clustering of Applications with Noise |
| FLS | Fuzzy Logic System |
| EWT | Empirical Wavelet Transform |
| ALI | Adversarially Learned Inference |
| GAN | Generative Adversarial Networks |
| SGD | Stochastic Gradient Descent |
| SAE | Sparse Autoencoder |
| SOM | Self-Organizing Map |
| NLP | Natural Language Processing |
| LIDAR | Light Detection and Ranging |
| NC | Numerical Control |
| ICT | Information and Communications Technology |

multi-modal features into a single feature. High-level fusion is based on integrating decisions from different models fitted to the data to develop a more reliable decision [13]. For multi-source information fusion, mid-level and high-level fusions are often carried out concurrently to enhance the quality of decision-making [14].

Traditional data fusion relies mainly on either probabilistic models, such as Bayesian networks and Dempster–Shafer (D–S) theory [15], or uncertainty models, such as rough set-based fusion [16]. With the advent of Machine Learning (ML) [17] and Deep Learning (DL) [18], a rapid evolution in data fusion techniques occurred. Likewise, the development of new hardware technologies, such as sensors and data processing systems, has resulted in many advances in data fusion techniques [19,20].

Below, several advantages of applying data fusion strategies in SHM are outlined:

- Reduce the redundancy in information obtained from different sources and, at the same time, provide complementary information.
- Facilitate the reduction in measurement time by decreasing the size of the data set.
- Compensate for the lack of information from a specific source during downtime and thus increase the reliability of SHM systems.
- Provide a higher signal-to-noise ratio (SNR) level by enhancing useful information and discarding redundancy and noise in the data.
- Reduce the uncertainty in measurements by providing complimentary information from multiple sources.
- Provide an enhanced picture of the medium subjected to monitoring.

The abovementioned benefits of data fusion can result in improvements in system identification and decision-making for a variety of reasons. Hence, it has been widely applied in different systems, including robotics [21,22], environmental monitoring [23], quality assurance [24], medical applications [25], manufacturing processes [7,26], traffic control [1], and SHM of complex systems [27]. Fig. 1 illustrates the distribution of data fusion applications in different fields of science between 2000 and 2023. In the figure, the percentage number represents the ratio of publications in each area to the total number of included publications on data fusion. Table 1 lists the applications of data fusion in different fields.

### *1.1. Overview of data fusion in SHM*

The first mathematical theories of data fusion were devised in the 1960s [38], and later, in the 1970s and 1980s, data fusion was implemented in various disciplines [39]. When it first appeared in the

**Table 1**
Applications of data fusion techniques in different fields (Num: Numerical study, Exp: Experimental study).

| Ref. | Method | Num. | Exp. | Application |
|---|---|---|---|---|
| Izadi et al. [28] | Fuzzy-based data fusion method | ✓ | ✓ | Reducing the energy consumption of a **Wireless Sensor Network (WSN)** whilst boosting the **Quality of Service (QoS)** in the network. |
| Ihnaini et al. [29] | DL-based data fusion method | ✓ | ✓ | Intelligent **healthcare recommendation system** to accurately predict diabetic disease. |
| He et al. [30] | data fusion method | ✓ | | Sustainable design of massage chair products to improve the performance of built-in **robots**. |
| Shi et al. [31] | Spatiotemporal data fusion method | ✓ | ✓ | Resolving the contrast between **satellite images**' temporal and spatial resolutions. |
| Barman et al. [32] | Bayesian data fusion method | ✓ | | **Damage detection** of large structures in noisy environments. |
| Yang et al. [33] | Spatiotemporal data fusion method | ✓ | ✓ | Estimating a daily Evapotranspiration (ET) of a field for **agricultural irrigation and water resource management**. |
| Jiang et al. [34] | DL-based data fusion method | ✓ | ✓ | Analysis and prediction of **drainage water quality**. |
| Jiang et al. [35] | Distance-probability classification (DPC) method | ✓ | ✓ | Building prediction models for classifying different hams for **food evaluation**. |
| Patil and Kumar [36] | AI-based data fusion method | ✓ | ✓ | Diagnosing different rice diseases automatically in the **agricultural domain**. |
| Saffari et al. [37] | Bayesian fusion method | ✓ | | Combining two **traffic data** sources to estimate the Macroscopic Fundamental Diagram (MFD) for a large-scale urban network. |

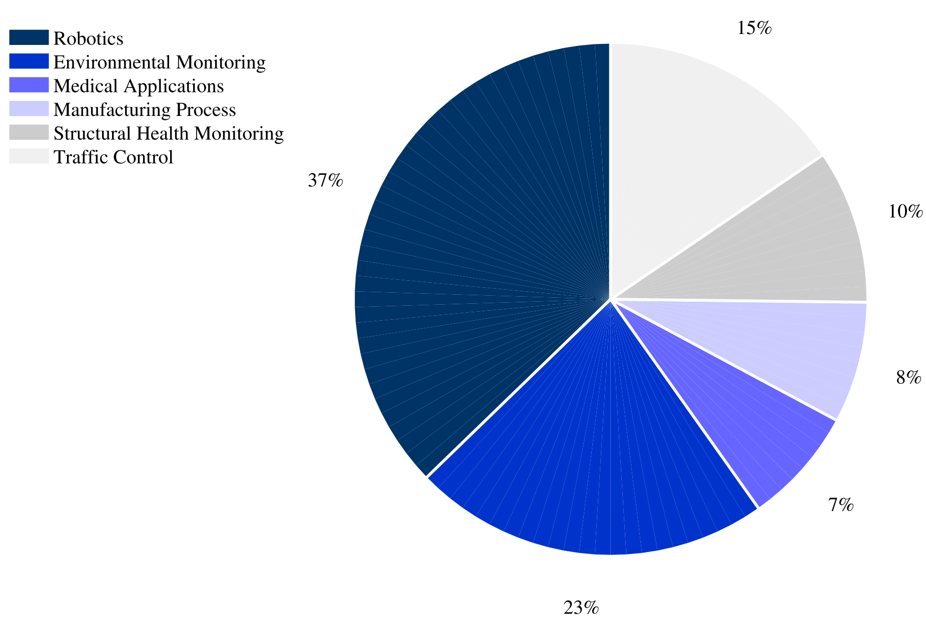


**Fig. 1.** Distribution of data fusion applications in different fields.

literature, the term "data fusion" did not yet have a specific definition. An information fusion sub-panel was thus manifested in 1984 in the USA, aiming to promote the concept of data fusion to the industry, identify requirements, organize conferences, and coordinate information fusion projects. According to a survey, numerous universities and enterprises worldwide have at least once performed research on data fusion and its application [19].

In the early years, only industries with significant capital could invest in research on data fusion. Hence, most of the early data fusion projects were devised in the military, where developments in man–machine interaction were sought to boost national defense efficiency. They aimed to reduce the demand for skillful operators who interpret information and make decisions while inspecting the battlefield or assessing a tactical situation. Data fusion applications have since extended to various fields, including non-destructive analytics, pattern recognition, robotics, earth sciences, medicine, and finance. More recently, the integration and fusion of multi-sensor information gained much popularity in SHM. Edwards et al. [40] first investigated the use of data fusion in SHM in 1993, and soon after, research interest swiftly increased across Europe [41]. While considerable research efforts have been invested in the last decade in applying data fusion in SHM, the full potential of this concept has yet to be exploited. Table 2 presents an overview of the history of data fusion in SHM from 2000 to 2023.

Fig. 2(a) illustrates the distribution of research papers from 2000 to 2023. There has been a notable increase in research on data fusion techniques in recent years. Additionally, Fig. 2(b) offers insights into the prevalence of research on machine learning-based and deep learning-based data fusion approaches. It is evident that there is a significant emphasis on both machine learning and deep learning, indicating their prominence compared to other data fusion methodologies.

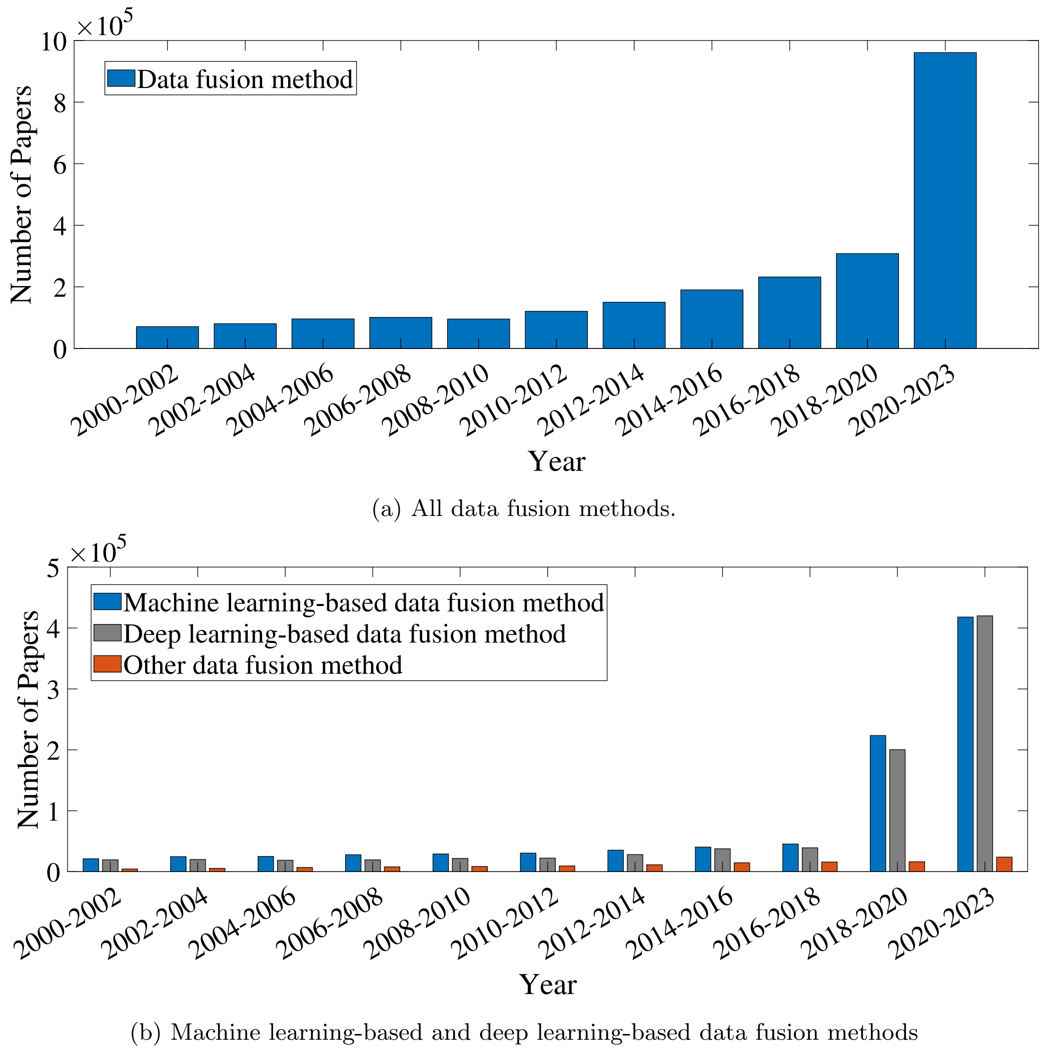


**Fig. 2.** Research trends in data fusion techniques.

In recent years, many studies have explored the use of data fusion techniques for SHM systems [42,43]. Yet, collectively leveraging new technologies has increased the demand for modern research that can tie data fusion's algorithmic advances to current SHM challenges. Several review articles on data fusion techniques, as listed in Table 3, have focused on specific aspects of the problem, such as the background mathematical theories. After studying the recent literature, the authors sensed a need for a comprehensive review of data fusion techniques for SHM. The current review article mainly focuses on applying advanced data fusion techniques for optimal SHM. Table 4 highlights the merits of the current study compared with recently published literature-review articles on using data fusion in SHM.

### 1.2. Research gaps and challenges

The development of new sensors has cultivated the availability of diverse data sources for SHM [80,81]. While much research effort has been invested in extracting critical information from the various types of recorded sensor data, many challenges are still faced in establishing robust decision rules using the aggregated data. Further, no universal agreement has been reached on a unique data fusion technique that can be applied equally well for all SHM problems in all systems. Therefore, before deciding on the type of data fusion technique for a specific SHM application, several factors need to be considered; these include (1) the format of the data, (2) the data quality, and (3) the expected goals of the data fusion.

Specific characteristics of the measured and recorded data are challenging for the implementation of data fusion. These challenges include the following:

1. The noise level and content of the recorded signals can vary. This effect can even occur with sensors measuring the same physical quantities or sensors produced by the same manufacturer.
2. Heterogeneous data sources can have inherently different data characteristics, revealing different aspects of system behavior but suffering conflicting types of data, incomplete data sets, and compromised conciseness of data.
3. Erroneous/Biased information can be present in recorded data when the sensors are poorly maintained or inappropriately used.

Over the years, several distinct data fusion techniques have been developed, such as the Bayesian probability framework [82,83], Dempster–Shafer (D–S) theory [84,85], Fuzzy logic [86,87], Machine learning models [88,89], and weighted combination and voting approach [90,91]. Advances in the Internet of Things (IoT) have resulted in the generation of large amounts of data [92,93], termed "big data" [94,95]. This vast volume of data prompted the exploitation of data fusion techniques for decreasing the data set size while extracting useful information. Thus, data fusion is a key step in advanced SHM methods [81], where data from different resources are combined to extract more succinct information about the health condition of the studied system. The

**Table 2**
History of data fusion in SHM (between 2000–2023).

| Ref. | Year | Method | Num. | Exp. | Description |
|---|---|---|---|---|---|
| Reichard et al. [44] | 2000 | Fuzzy logic | ✓ | ✓ | This work proposes a distributed machinery condition monitoring system and presents system architecture, data fusion method, and classification algorithms. The method is applied to a distributed, wireless bearing and gear health monitoring system. |
| Mahajan et al. [45] | 2001 | Fuzzy logic | ✓ | | This paper describes a unique technique for fusing information from multiple sensor networks with a fuzzy logic inference system. |
| Dempsey et al. [46] | 2002 | Data fusion Analysis | ✓ | ✓ | This paper presents a diagnostic tool with data fusion strategies for detecting spiral bevel gear damage. |
| Ou and Li [47] | 2003 | Signal fusion analysis | | ✓ | This work presents an offshore platform health monitoring system with a wireless sensor network. A laboratory prototype with signal fusion is used to show the validity and feasibility of the proposed WSN. |
| Joubert and Bihan [48] | 2004 | pixel level data fusion | ✓ | ✓ | This paper proposes to fuse eddy current (EC) data from an oriented field sensor and maximum likelihood (ML) fusion rule to detect defects in riveted lap joints. |
| Chun et al. [49] | 2005 | Neural networks | ✓ | | This paper proposes a two-layer neural network for information fusion to facilitate damage detection. |
| Jiang et al. [50] | 2006 | Decision data fusion | ✓ | | This work presents a five-phase method for detecting complex structural damage utilizing data fusion techniques and a probabilistic neural network (PNN). |
| Smyth and Wu [51] | 2007 | Kalman filtering | ✓ | | This work presents an approach for estimating the velocity and displacement from noise-contaminated acceleration and displacement measurements using a Kalman filtering and smoothing method. |
| Li et al. [52] | 2008 | Dempster–Shafer (D–S) evidence theory | ✓ | | This work develops a damage identification technique through artificial neural networks (ANN), Shannon entropy, and employs D–S evidence theory to fuse the system's information. |
| Lu and Michaels [53] | 2009 | Feature data fusion | ✓ | ✓ | This paper evaluates differential features derived from diffuse ultrasonic signals based on feature threshold detection with voting techniques. |
| Zhao et al. [54] | 2010 | D-S theory | ✓ | ✓ | This work presents a hierarchical ensemble scheme using the Rotation Forest (RF) technique and the D-S theory to fuse data. |
| Dackermann et al. [55] | 2010 | Neural Network Ensemble | ✓ | ✓ | This paper proposes a hierarchical neural network strategy to merge modal information from different sensors for damage identification. |
| Jiang et al. [56] | 2011 | PNN models | ✓ | | This work presents a new hybrid data fusion technique for damage detection using the Probabilistic Neural Network Model (PNN) data fusion method. |
| Banerjee and Das [57] | 2012 | SVM | ✓ | ✓ | This article investigates a new hybrid strategy for fault signal classification based on sensor data fusion, Short Term Fourier Transform (STFT), and Support Vector Machine (SVM) methods. |
| Vanniamparambil et al. [58] | 2013 | Feature data fusion | ✓ | ✓ | This article describes a data fusion technique based on Digital Image Correlation (DIC) and Acoustic Emission (AE) to identify progressive damage evolution in reinforced concrete masonry walls (CMW) considering different types of reinforcement. |
| Grande and Imbimbo [59] | 2014 | D-S technique | ✓ | | This article presents a linear system condition monitoring method using modal strain energy (MSE) and classical damage indicators based on multilevel information fusion techniques. |
| Ferrari et al. [60] | 2015 | Kalman filtering | ✓ | ✓ | This work presents comprehensive processing of response signals obtained from an experimental campaign on a local historical bridge using four types of sensory strategies and data fusion using a dedicated MultiRate Kalman filtering strategy. |
| Mishra et al. [61] | 2016 | Bayesian method | ✓ | ✓ | This work proposes a damage identification method using regularized linear discriminant analysis strategy based on the Bayesian method. |
| Santos et al. [62] | 2017 | Decision methods | ✓ | ✓ | This work presents a new hybrid data-driven technique based on pattern recognition and data fusion techniques for SHM of a cable-stayed bridge. |
| Guo and Xu [63] | 2018 | D-S evidence theory | ✓ | ✓ | This article presents a new method for identifying damage in 1D and 2D systems based on the D-S theory algorithm. |
| Ding et al. [64] | 2019 | Improved D–S algorithm | ✓ | ✓ | This work presents an improved Dempster–Shafer data fusion algorithm to solve the counter-intuitive evidence theory problems and improve the fusion results' reliability. |

(continued on next page)

**Table 2** (*continued*).

| | | | | | |
|---|---|---|---|---|---|
| Dabetwar et al. [65] | 2020 | Deep neural networks | ✓ | ✓ | This paper employs Deep Neural Networks (DNNs) and data fusion to develop a reliable damage detection technique for composite structures. |
| Fu and Jiang [2] | 2021 | PNN | ✓ | ✓ | This work proposes a novel hybrid data-fusion damage identification strategy based on an intelligent model that fuses data for arch bridge systems using fractal dimension (FD) and probabilistic neural network (PNN) integration. |
| Dabetwar et al. [66] | 2022 | Deep Neural Networks | ✓ | | An approach based on artificial intelligence techniques and Lamb wave measurements is proposed for the fault identification of complex systems such as composite materials. |
| Wang et al. [67] | 2023 | Feature-level fusion | ✓ | ✓ | This paper proposes a novel method for identifying modal parameters of arch dams by fusing information at multiple levels. |

**Table 3**
Summary of recent literature reviews on data fusion.

| Ref. | Journal | Description | Focus |
|---|---|---|---|
| Zhang et al. [16] | Information fusion | This paper reviews state-of-the-art literature on the developments in Multi-source Information Fusion (MSIF) under the Rough Set Theory (RST). | Theory |
| Liu et al. [18] | Information fusion | This study presents three categories of DL methods for urban big data fusion: DL input, output, and double-stage fusions. | Application |
| Alam et al. [68] | IEEE Access | This work discusses different mathematical tools for information fusion in the IoT domain, including probabilistic approaches, artificial intelligence methods, and theory of belief. | Theory & application |
| Broer et al. [69] | Aerospace | This work presents how multisensor data fusion concepts can advance SHM of composite structures and thereby transition the aircraft industry towards condition-based maintenance strategies. | Application |
| Ding et al. [70] | Structural Control and Health Monitoring | This review proposes a set of requirements for IoT data fusion, including security and privacy requirements. The IoT applications are classified into several domains, and the state-of-the-art of data fusion in critical IoT applications is discussed. | Application |
| Ghamisi et al. [14] | IEEE Geoscience and Remote Sensing Magazine | This paper applies multisensor and multitemporal data fusion in various applications, including point cloud data fusion, pansharpening and resolution enhancement, hyperspectral and lidar data fusion, big data and social media, and multitemporal data fusion. | Application |
| Wu and Jahanshahi [71] | Structural Health Monitoring | This article comprehensively reviews data fusion approaches applied in SHM systems. It starts with the basic definitions of prevailing data fusion techniques and then examines each method's applications. | Theory & application |
| Krishnamurthi et al. [72] | Sensors | Several technologies, including edge computing, fog computing, and cloud computing, are reviewed, and their challenges for data fusion in IoT sensor networks are discussed. | Theory & application |
| Nsengiyumva et al. [73] | Structural Control and Health Monitoring | This paper discusses recent advances in data fusion nondestructive evaluation (NDE) to meet quantitative NDE accuracy and reliability needs, particularly for inspecting primary and secondary load-bearing structures. | Theory & application |
| Mu et al. [74] | Sensors | This paper presents data and learning indicators applied in Multimodal learning analytics (MMLA), classifications of different data fusion methods in MMLA, and their relationships. | Theory & application |

**Table 4**
Summary of the areas covered in recent literature reviews on the application of data fusion in SHM. (Refs: References, DF: Data Fusion, Det: Detailed, Class: Classifications, App: Applications, Sen: Sensors, Meas: Measurements, Tech: Techniques, DL: Deep Learning).

| Ref. | Det SHM | Det Meas | Det Sen | Det DF | App of DF | Class of DF | DF Tech | DL based DF | DF in smart city |
|---|---|---|---|---|---|---|---|---|---|
| **Our review paper** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Broer et al. [69] | ✓ | | | ✓ | ✓ | ✓ | | | |
| Wu and Jahanshahi [71] | | | | ✓ | ✓ | ✓ | ✓ | | |
| Kralovec and Schagerl [75] | ✓ | | | | ✓ | | | | |
| Nsengiyumva et al. [73] | ✓ | | | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Chen et al. [76] | ✓ | | | ✓ | ✓ | ✓ | ✓ | | |
| Dalla Mura et al. [77] | | | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Li et al. [4] | | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Ghassemian [78] | | | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Duan et al. [79] | ✓ | | | ✓ | ✓ | ✓ | ✓ | | |
| Adamopoulos and Rinaudo [42] | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | |

application of various data fusion techniques is faced with several challenges, such as:

- The Bayesian probability framework and the state estimation method often rely on subjective decisions about the model selection and the prior probabilities. The techniques' efficiency depends on the choice of models, prompting sensitivity analysis for testing robustness. Further, uncertainties arise with the estimation of the prior probabilities.
- The D-S theory relies on a subjective choice of frame of discernment, the loose selection of which, along with inappropriate combination rules, could result in unpredictable fusion outcomes.
- The fuzzy logic algorithm requires well-defined production rules and membership functions to produce fair inference.
- Machine learning (ML) models need sufficient and balanced samples for training, validation, and testing to obtain a system's general characteristics.
- Like the weighted combination approach, the voting approach requires the determination of suitable weights for each sensor data. Although constant weights can aggregate information from multiple sources, long-term condition monitoring demands a dynamic weight calibration scheme.
- Utilizing a fixed threshold for the time-varying data can bear unreliable damage detection results. Thus, making reliable inferences from the fused results requires the selection of appropriate thresholds.

### 1.3. Objectives of this study

The vast amount of heterogeneous data available from various sensors deployed on a system increases the diversity of information. This development provided new opportunities for SHM. However, the interpretation of the diverse data types for system health estimation and damage identification presents many challenges in the development of reliable SHM techniques. Aggregating information from multiple sensors facilitates robust decision-making about the structural health condition by extracting more useful information from the data fusion process. Hence, implementing data fusion techniques is a critical step in advanced SHM.

This article systematically reviews the history of research on data fusion developments for SHM of civil infrastructures. A great number of literature reviewed in this paper provided rich resources for the investigation of their effectiveness. Moreover, the readers are provided with the concepts of various data fusion techniques and their application for reliable SHM. Besides, as complementary tools, tables are meant to emphasize the perspective of data fusion techniques standing behind the SHM literature. The main contributions of this paper can be summarized below:

1. Present the main definitions in data fusion and all classifications based on different criteria.
2. Review recent literature on data fusion-based SHM and discuss the advantages and disadvantages of proposed methods.
3. Present the applications of different data fusion methods in various fields and outline their benefits/challenges.
4. Explain in detail advanced data fusion methods and their applications in SHM.
5. Provide a comparative overview for evaluating different articles on data fusion-based SHM.
6. Based on the knowledge acquired from this comprehensive review, we discuss significant open problems and present roadmaps for future research on data fusion.

The following outlines of the remaining sections of this paper:

- Section 2 introduces the topic of data fusion and its application in SHM.
- Section 3 presents background knowledge on data fusion methods in SHM.
- In Section 4, we detail the concepts of Multimodal data fusion presenting various classification methods techniques, and relevant literature.
- Section 5 presents traditional data fusion techniques, including probability-based, knowledge-based, and evidence-reasoning methods, reviewing the structure, application, advantages, and disadvantages of respective methods.
- Section 6 discusses the application of Artificial intelligence for data fusion in SHM.
- In Section 7, a set of criteria was proposed for comparing different original and review papers in this field. In this section, we compare all of the papers cited in this paper.
- In Section 8, we summarize data fusion applications in smart cities.
- Section 9, outlines the challenges of data fusion and discusses future research directions identified from our literature review.
- Section 10, describes trends and future developments in data fusion methods.
- Finally, in Section 11, we provide concluding remarks.

### 1.4. Criteria set for paper selection

The criteria used to select the most important papers play an essential role in ensuring the integrity, relevance, and comprehensiveness of a review article. A set of structured criteria guides the process of selecting articles from a large pool of available literature. Many factors contribute to the importance of well-defined selection criteria, including:

- Relevance and Scope: These criteria allow reviewers to focus on articles that align with the scope and objectives of the review. Choosing papers based on the key themes, topics, and research questions of interest ensures that the papers selected provide meaningful contributions to the review's overall objective.
- Quality Control: Rigorous selection criteria are essential for ensuring the quality of the reviewed articles. By establishing benchmarks for methodological rigor, empirical validation, and scholarly contribution, the criteria help in filtering out papers that may lack robustness or rigor.
- Avoiding bias: Employing clear and transparent selection criteria assists in minimizing the impact of bias on the evaluation process. By clearly stating the inclusion criteria, reviewers can increase the credibility and reliability of the findings and ensure that their choices are objective and impartial.
- Focused Analysis: The use of well-defined criteria enables reviewers to identify articles that share common attributes, methods, or themes. Consequently, the literature can be analyzed in a more structured and insightful manner, resulting in more coherent discussions and more meaningful conclusions.
- Transparency: Clearly articulating the selection criteria enhances the transparency of the review process. Readers are able to gain a deeper understanding of the methodology behind the review, thereby promoting openness and facilitating a more critical evaluation of the review.

In order to compulsively and systematically reflect the scope and trend on the topic, a set of criteria has been developed to help systematically select papers for this review article. Fig. 3 summarizes the process flow of the various steps involved in selecting, researching, and introducing this review article. In Table 5, the inclusion and exclusion criteria that we implemented for selecting the reviewed articles are presented.

Applying the criteria outlined above, this review paper reviewed a total of 489 papers for this review analysis.

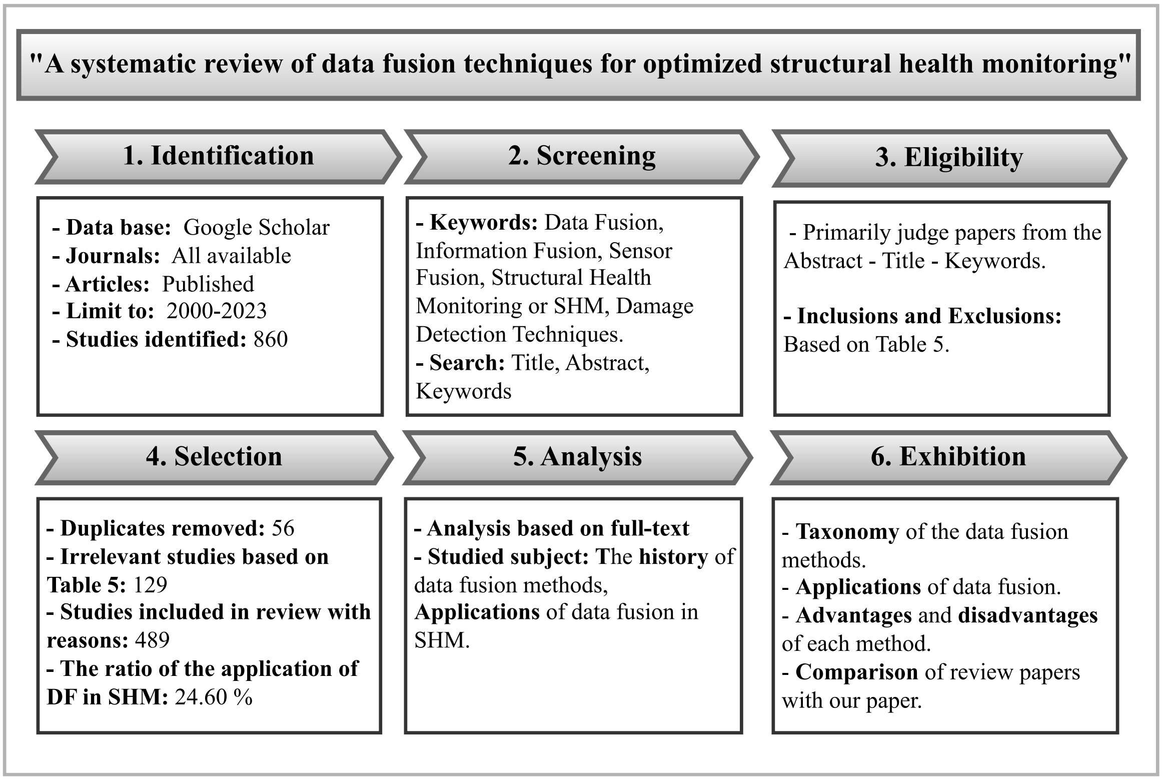


**Fig. 3.** Process for selecting, researching, and analyzing this literature review.

**Table 5**
Exclusion and inclusion criteria for selecting reviewed articles.

| Inclusion criteria | Exclusion criteria |
|---|---|
| The following search keywords are included in the title, abstract, or keywords:<br>• "Data Fusion Techniques"<br>• "Structural Health Monitoring"<br>• "Damage Identification Methods"<br>• "Information Fusion Approaches" | • Studies published before 2000.<br>• Duplicated papers (only one paper included).<br>• Articles unrelated to data fusion.<br>• Non-English papers.<br>• Papers not peer-reviewed.<br>• Poor quality papers |

## 2. Overview of data fusion for SHM

Structural health monitoring (SHM) [96] is typically conducted on five principal levels: (1) Detection: qualitative indication of damage presence, (2) Localization: estimation of damage location, (3) Classification: determination of damage type, (4) Quantification: assessment of damage severity, (5) Prognosis: estimation of the remaining service life of the structure. The overall aim of SHM is to ensure structural safety and maintain the structure's integrity for as long as possible. The following elements are the main building blocks of an SHM system that should be considered when implementing data fusion [97]:

- Sensors: They collect the response of a structure excited by an external force and are either permanently or temporarily embedded/mounted to the structure Data fusion is dependent on the type of sensors deployed in the system. The degree of sensor diversity results in heterogeneity in the collected data that needs to be appropriately addressed in the fusion stage.
- Control system: It stores and manages a variety of heterogeneous data [98].
- Data processing unit: The stored data is analyzed by this unit to infer possible damage. Features extracted from fused heterogeneous data are beneficial for health assessment.

Before deciding on the type of monitoring platform, three key factors must be considered: the monitoring time frame, the monitoring scale, and the data fusion algorithm. The time frame usually refers to one of the following concepts:

- **Short-term monitoring**: Short-term goals are sought using the monitoring of the system response information [99].
- **Long-term monitoring**: Long-term objectives are pursued through monitoring system response over a long time period to detect any possible anomalies in the structural response that can be referred to as damage [100].
- **Inspection**: Regular inspections are carried out to monitor the system components [101].
- **Early warning**: An early warning alarm is implemented. Here, extracted features violate pre-defined thresholds, informing the user of possible damage [102].
- **A collapse warning**: This warning signal raises the alarm when there is a risk of system collapse. It will result in the system's closure [103].

The monitoring scale typically targets the following components:

– **Local**: Refers to a monitoring paradigm that focuses on a specific region.
– **Member**: Is defined as a particular system component targeted for monitoring.
– **Global**: Refers to the monitoring of the entire system.

Data fusion can maximize the information extracted from the recorded data of the structure [73]. Although the data processing unit is the primary unit for data fusion, data fusion can be implemented at various processing steps in the SHM system. For example, sensor fusion fuses data extracted from different sources (sensors). Using hardware for sensor fusion has been used for space applications [104] Data fusion can favor the condition assessment of an object, such as a rover, on other planets [105]. Sensor data fusion has been extensively implemented in autonomous vehicles. The controlling system of these vehicles integrates multi-source data, such as radar sensors and multipurpose cameras, for the robust navigation of surrounding objects [106,107].

In general, adopting an efficient data fusion strategy follows a procedure that answers the following questions:

- Which is the optimal SHM technique that can be appropriately applied for damage detection of the system of interest?
- Which features are sensitive to damage?
- How can the data be appropriately fused in the chosen fusion architecture?
- What level of reliability and accuracy can the adopted data fusion technique provide?
- What are the environmental and operational effects on the studied data and its fused version?
- What operational range can the defined data fusion framework cover?
- How can the data fusion reliability and accuracy be dynamically optimized?

One needs to be careful not to confuse the notion of data fusion with information fusion. While data integration mainly combines collected data to increase data consumption, the primary aim of information fusion is to provide data abstraction. In other words, data fusion retains the entirety of the data. In contrast, information fusion aims to reduce the amount of undesirable data to provide only desirable and valuable data for confident decision-making. Information fusion practices thus incorporate the human analytical capability to reduce uncertainty. This process is featured in the last step of an SHM system, where a human-developed analytical technique is used for decision-making [4].

### 2.1. Measurement types

This section discusses typical measurement types suitable for data fusion-based SHM. To adequately monitor a structure's health, multiple types of system responses may be required based on the structure type and the requirements of the system owner. The performance and health of a structure are generally assessed from specific structural data types. Some measurement quantities are explicit for concrete and steel structures, while others can characterize faults in any structure. It is essential to recognize the contribution of each measurement type for different monitoring systems [108]. Below, popular measurement types, their definitions, and characteristics are presented:

- **General measurements:**
  - Displacement: Refers to the movement of a point in a system with respect to its initial location.
  - Acceleration: The rate of velocity change in a vibrating point in a system.
  - Climatic parameters: These aim to parameterize the environmental conditions in a specific system district.
  - Tilt/slope: Refers to an angular dislocation of a point.
  - Curvature: Indicates the first derivative of a specific location's slope on an externally loaded system.
  - Load: An external force such as acceleration or displacement loading for dislocating a point.
  - Scour: This is defined as the phenomenon of soil removal around the piers of a system in a flood event.

  It is known that environmental variations can mask the effect of damage on the structural response. Therefore, Bao et al. [109] proposed a data fusion-based damage identification method considering temperature variations in the structure–environment system. The proposed technique is based on the Bayesian inference of temperature and structural modal properties, i.e., the structural eigenvalues. The probability density functions of these parameters are derived to be further used for damage detection. The inconsistency of the damage detection results from different sets of temperature and modal data prompted the use of a decision rule for robust damage detection. The D–S evidence theory was employed to make a consistent decision by integrating inconsistent damage detection results from the data sets recorded at different times
- **Measurement for concrete structures:**
  - Corrosion: Describes the concrete depletion level due to carbon dioxide or chloride formation processes.
  - Cracking Parameters: This term refers to specific damage characteristics, such as length, width, and the number of cracks based on the level of separation of the concrete system from the surface of a member.
  - Rebar Delamination: This refers to the position of the corrosion in concrete around the metal reinforcement (rebar).
  - Strain: Defines the relative length change at a specific location of a member.
  - Strength: A measure of strength characteristics of cylindrical or cubic samples in the laboratory, obeying the properties of the concrete mixture cast in situ.
  - Tension: Characterizes the tension in rebar or tendons of post-tensioned structures.

  As a highly heterogeneous material, concrete is susceptible to various physical, chemical, and mechanical degradation processes. Damage detection of this material demands integrating different types of heterogeneous data. For example, Liang et al. [110] employed several fusion techniques, including fuzzy analytical hierarchy, information entropy, and the Dempster–Shafer theory, to integrate mechanical responses with visual inspection results for damage detection in prestressed concrete bridges.
- **Measurements for steel structures:**
  - Corrosion: Refers to the chemical reaction between the steel and corrosive matter in the system.
  - Crack Growth: The propagation of a crack in a member.
  - Cracking: This is defined as the rupture of a macroscopic matter by the accumulated stress caused by cyclic loading.
  - Strain: Refers to the relative length changes in a component due to externally applied loads.
  - Cable tension: This is defined as the amount of tension along a cable in cable-stayed systems.

As discussed earlier, SHM can vastly benefit from sensor network fusion. This is, in particular, the case for steel structures. For instance, Singh et al. [111] proposed a sensor network-based optimized data fusion approach. The proposed method employs electromechanical impedance (EMI) signals to monitor metallic structures. To this end, various piezoelectric transducer parameters, including admittance, impedance, conductance, and resistance in the frequency domain, were analyzed through principal component analysis to derive the corresponding root mean square deviation index. A baseline was prepared based on the centralized fused-data eigenvector. Then, damage indices were derived by projecting the fused information on the baseline model.

**Table 6**
Main characteristics of sensors in SHM systems.

| Characteristics | Definition |
|---|---|
| Range [117] | The range of a sensor refers to the variation of the measured quantity between a minimum and maximum value. |
| Sensitivity [118] | The degree of sensor response to a change in a structure due to applied loads. |
| Accuracy [119] | The degree of the preciseness of a sensor in measuring a quantity |
| Stability [120] | This is defined as the durability of the sensor networks in long-term monitoring of a system. |
| Repeatability [121] | The degree of the variability of data read by a sensor when the structure is subjected to the same loading scenario |
| Energy Harvesting [122] | The capability of sensors to self-operate through harvesting the energy of a vibrating structural system. |
| Compensation due to variations in environmental and operational conditions (EOCs) [123] | The ability of a sensing network's signal conditioning to reduce the effects of EOCs. |

### 2.2. Sensor types and selection for data fusion-based SHM

This section outlines the essential requirements for selecting sensing systems for SHM and highlights challenges specific to the implementation of data fusion. An SHM system generally involves two major processes, (1) sensing: to measure structure-dependent data, and (2) data analysis: to identify damage-sensitive features from the measured data used to identify any damage in the structure. Ideally, the recorded quantities are highly sensitive to low levels of damage, insensitivity to environmental and operational variations (EOVs), and robust to measurement noise [112,113]. The significance of EOV remains a critical concern within the SHM domain. These variations directly impact the efficacy of damage diagnosis across multiple dimensions, encompassing early damage detection, precise damage localization, and accurate damage quantification. A detailed discussion of the different SHM methods that consider the effects of EOVs can be found in [96,114–116]. For data fusion-based SHM, the sensor network must further fulfill data fusion strategy requirements. For system design, generally, four critical issues need to be considered: (1) the monitoring duration, (2) the time scale of damage evolution, (3) the adverse effects of EOVs, and (4) the cost of adopting the system. The following characteristics must be taken into account for the design of the suitable sensing network:

- Types of measurements to be captured,
- Sensor types, numbers, and locations,
- Bandwidth, sensitivity, and dynamic range,
- Telemetry, data acquisition, and storage system,
- Power demands,
- Continuous or periodic sampling intervals,
- Memory and processor requirements,
- Signal conditioning,
- Excitation source in active sensing.

Table 6 lists the main characteristics of sensors typically used in an SHM system.

The selection of the sensor types and size of the sensing network is critical and must be determined before specifying other design requirements. Moreover, some standards must be considered for the proper sensing system design regardless of the applied method, e.g., vibration-based [124,125], ultrasonic-based [126], strain-based [127,128], or combined [129]. Some standard-related considerations include:

- The sensitivity of measurements to the malfunction of the monitoring system.
- The sensitivity of sensors to long-term EOC variations, such as humidity and temperature.
- The sensitivity of sensors to chemical and/or mechanical factors.

Adopting existing technology to achieve an efficient sensing network is a challenging task. For example, efforts are being made to develop new self-powered sensors that can record various types of measurement quantities while withstanding severe weather conditions [130]. On the other hand, using a heterogeneous sensor network comprising a variety of multiple sensor types presents several advantages, including:

- It increases the robustness of the intended measurement.
- It enhances the system's reliability in the downtime of a particular network.
- In many monitoring cases, a large number of low-precision measurements is preferred to a small number of high-resolution measurements.
- It reduces uncertainty in the monitoring results.

However, a large volume of sensors also comes with disadvantages, including the following:

- The large volume of data exchange increases the power consumption of the sensor network.
- The extended network is more prone to EOC effects.
- It is more challenging to manage the massive volume of information.

There is a trade-off between the number of sensors used and the quality of information gathered for an application. The choice of the specific sensor types used for an SHM system is determined based on the required measurement quantity. Table 7 presents different measurement types and suitable sensors.

The accuracy of data fusion methods directly depends on the accuracy of the collected data from sensors. Hence, selecting the appropriate type of sensing system to collect the monitoring data is a fundamental issue [81]. Table 8 presents an overview of sensors previously used for data fusion strategies, associated output formats, and applied data analysis methods.

#### 2.2.1. Sensor fusion hardware

The term sensor fusion hardware refers to devices and components that facilitate the acquisition and processing of data from various sensors. In an SHM system, sensor fusion hardware systems collect, synchronize, and aggregate data from multiple sensors installed on infrastructure such as buildings or bridges. Such systems combine data streams from various sensors, including accelerometers, strain gauges, temperature sensors, cameras, and more. Sensor fusion hardware improves the accuracy, reliability, and efficiency of data collection and processing, and can provide an accurate and comprehensive understanding of structural behavior and health.

**Table 7**
Measurement types and suitable sensors for the SHM system.

| Measurement type | Sensor type |
|---|---|
| Displacement | Gyroscope [131,132], Ultrasonic [133,134], Inductive [135,136], Acoustic emission [137,138], Capacitive [139,140], Magnetic Optical [141,142] |
| Velocity | Magnetic induction [143,144], Optical [145,146], Piezoelectric [147,148] |
| Acceleration | Piezoresistive [149,150], MEMS [151,152], Piezoelectric [153,154], Capacitive [155,156] |
| Strain | Piezoresistive [157,158], Optical [159,160] |
| Force | Optical [161,162], Piezoresistive [163,164] |
| Temperature | Optical [165,166], Acoustic [167,168], Thermoresistive [169,170], Thermoelectric [171,172] |
| Pressure | Piezoresistive [173,174] |

**Table 8**
Review of sensors used in data fusion strategies based on the output format.

| Sensor | Output format | Data analysis method | Ref. |
|---|---|---|---|
| Optical sensor | Image | DL-based data fusion | Schmitt et al. [175] |
| Radar | Pulse signal | Unmanned aerial vehicle (UAV) swarm | Wan et al. [176] |
| Infrared sensor | Image | Kalman filter | Conde et al. [177] |
| Satellite | Image | Panchromatic image | Grochala and Kedzierski [178] |
| Ultrasonic sensor | Pulse signal | Extended Kalman Filtering (EKF) | Wang et al. [179] |
| NDT sensor | Voltage | Bayesian methodology | Ramos et al. [180] |
| Sonar | Pulse echo | Deep Neural Networks-based data fusion | Dos Santos et al. [181] |
| Laser | Image | Wavelet transform-based data fusion | Pradhan et al. [182] |
| X-ray | Image | Dempster–Shafer theory | Ben Atitallah et al. [183] |

A sensor fusion system is composed of a range of components, such as PIC microcontrollers, data acquisition units, communications interfaces, and processing units. Using these components, raw sensor data is captured and preprocessed, synchronization mechanisms are applied, and potential data processing tasks are performed. Following that, the data is sent to a decision-making or analysis stage. Sensor fusion hardware can be classified into the following types:

- Data Acquisition Systems (DAS): These are essential hardware components for collecting raw data directly from sensors. DAS units utilize analog-to-digital converters (ADCs) for converting analog sensor signals into digital formats that can be processed by a computer or microcontroller.
- Microcontrollers and Processors: These components manage information collected from various sensors. Data synchronization, initial data processing, and communication between systems are all facilitated by microcontrollers and processors.
- Sensor Hubs: These hubs are composed of microcontrollers or processors that handle data from multiple sensors simultaneously. Such systems manage sensor output, perform simple fusion algorithms, and transmit processed data to higher-level systems.
- Embedded Systems: These systems are complete computing platforms that include microcontrollers, processors, memory, communication interfaces, and sometimes hardware accelerators. Embedded systems are capable of processing sensor data, integrating algorithms, and making real-time decisions.
- Field Programmable Gate Arrays (FPGAs): These hardware components can be programmed to perform specific functions. By implementing custom algorithms and data processing pipelines, they can be optimized for sensor fusion tasks.
- Digital Signal Processors (DSPs): These processors efficiently handle digital signal processing, making them ideal for the fusion and processing of sensor data. The Incorporated algorithms can reduce noise, filter data, and extract features.
- Communication Interfaces: Sensor fusion hardware frequently includes communication interfaces for exchanging data with other systems. Ethernet, USB, and Wi-Fi are examples of wired and wireless interfaces (e.g., Bluetooth, LoRa).
- Hardware Accelerators: These are specialized components that speed up specific computations, such as matrix operations and machine learning. Hardware accelerators can significantly enhance the speed and efficiency of processing and fusing sensor data.
- Smart Sensor Networks: Certain sensors possess processing capabilities that enable them to perform initial data fusion at the sensor level. With the integration of smart sensor networks, it is possible to enhance data fusion accuracy and reliability.
- Custom Hardware Solutions: Customized sensor fusion hardware solutions can be designed and developed to address unique challenges and achieve optimal performance depending on the application.

In summary, the use of sensor fusion hardware can improve real-time monitoring capabilities, reduce data transmission and storage requirements, enhance signal quality, and handle more sensors simultaneously. Moreover, as hardware technology advances, it presents opportunities for developing more energy-efficient and cost-effective solutions, leading to a more widespread implementation of SHM systems.

## 3. Data fusion concepts

The terms "data fusion", "sensor fusion", and "information fusion" are commonly used to describe the process of combining data from multiple sources. The following are the distinctions between these terms:

- Data Fusion: In this process, data from multiple sources, usually sensors (in the context of SHM), are combined to construct a more comprehensive and accurate representation of a phenomenon. The primary objectives of data fusion are to reduce noise, enhance accuracy, and improve the overall data quality. Data points are consolidated to generate a unified dataset, providing a more accurate representation of the system being monitored.
- Information Fusion: This broader concept combines not only sensory data but also contextual information, such as expert opinions, historical data, and even non-sensory information from databases, reports, or texts.
- Sensor Fusion: This is a subset of data fusion that focuses explicitly on the integration of data from different sensors. The purpose of sensor fusion is to combine the outputs of multiple sensors to assess systems more reliably and comprehensively.

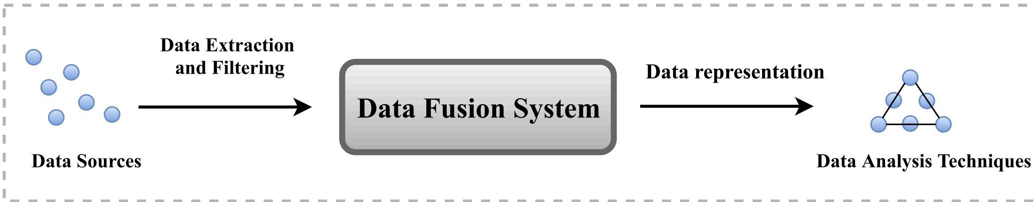


**Fig. 4.** General data fusion concept.

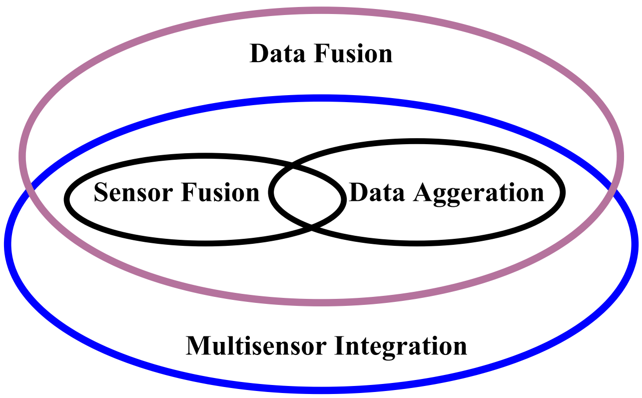


**Fig. 5.** Relationship between multisensory fusion, sensor fusion, data aggregation, and data fusion.

The following section provides background information and comprehensive definitions of data fusion concepts and their taxonomies in SHM systems. The goal of data fusion is to achieve more accurate, consistent, and valuable information than can be provided by any single data source alone. Fig. 4 illustrates the generic concept of data fusion. In general, a data fusion system is positioned between the two stages of data filtering and processing. According to Fig. 5, it is possible to establish a connection between the domains of multisensory fusion, sensor fusion, data aggregation, and data fusion, which even overlap in some areas. Different definitions of the term fusion exist in the literature, although the definitions largely overlap [70]. The essential processes of data fusion include:

– **Purpose**: First, the purpose of performing data fusion needs to be defined.
– **Data sources**: Next, the data type required for the defined purpose must be chosen, and appropriate sensors to serve the purpose selected.
– **Operation**: Finally, an algorithm must be adopted or developed to conduct the soft computing for the data fusion system.

The implementation of data fusion strategies in SHM can have many benefits; these include the following:

– It increases damage detectability and ensures reliability,
– It broadens the range of spatiotemporal inference from the data set,
– It reduces the inference ambiguity,
– It improves the accuracy of detection,
– It optimizes the dimension of the target features.

### *3.1. Types of data fusion techniques*

This section discusses the most common data fusion techniques. Conceptually, data fusion strategies can be devised based on different factors such as sensor relations, input–output relations, and decision relations (see Fig. 6). Fig. 7 presents the most common data fusion classifications considering different processing levels, i.e. Whyte's classification, Dasarathy's classification, JDL classification, Architecture classification, and Abstraction classification. Fig. 8 illustrates the number of papers for all classifications between 2000 and 2023. The visual representation clearly indicates the prominent level of interest and research focus of Whyte's classification compared to other techniques. The following sections describe details of each category of data fusion based on the type and applications in SHM systems.

#### *3.1.1. Whyte's classification*

Durrant-Whyte [184]] classified sensor fusion methods into three categories based on sensor network relations: Complementary fusion, redundant fusion, and cooperative fusion, which offer different approaches for integrating data from multiple sources in optimized SHM systems. Complementary fusion leverages the complementary nature of data to provide a complete representation of the structural health condition, redundant fusion enhances reliability and robustness through redundancy, and cooperative fusion enables collaboration and communication among different data sources. Further research and development in these areas can contribute to the advancement of optimized SHM techniques and improve the overall performance and effectiveness of SHM systems. The classes, illustrated in Fig. 9, are defined as follows:

– **Complementary fusion**: An effective data fusion approach involves integrating disparate data sources to achieve a more accurate and reliable representation of a phenomenon. The concept behind this method is that different data sources possess varying strengths and weaknesses, which, when combined, can provide a more comprehensive and balanced perspective. As an example, Jin et al. [185] developed a complementary data-fusion algorithm based on Gaussian process regression in the form of an auto-regressive scheme for point and distributed strain sensors, to combine their advantages and predict accurate strain distributions (i.e., high accuracy and high-spatial-resolution). Complementary fusion results in a cohesive, robust representation of the environment that capitalizes on the strengths of each sensor while mitigating their individual weaknesses. This approach finds applications in numerous domains, including robotics, environmental monitoring, healthcare, and military systems, where precise and reliable information is critical for effective decision-making. The following provides an overview of complementary fusion characteristics:
  – Distinct and Complementary Capabilities: The data sources are assumed to have unique and complementary capabilities or sensing modalities. For example, one data source may provide information about temperature, while another may provide information about pressure. By combining these complementary data, the fusion process aims to obtain a more comprehensive and accurate understanding of the phenomenon being monitored.
  – Feature-Level and Decision-Level Fusion: The complementary fusion of data can be achieved in two distinct ways: feature-level fusion and decision-level fusion. Feature-level fusion seamlessly merges features extracted from various data sources, while decision-level fusion integrates decisions or outcomes from these sources, resulting in a final decision.

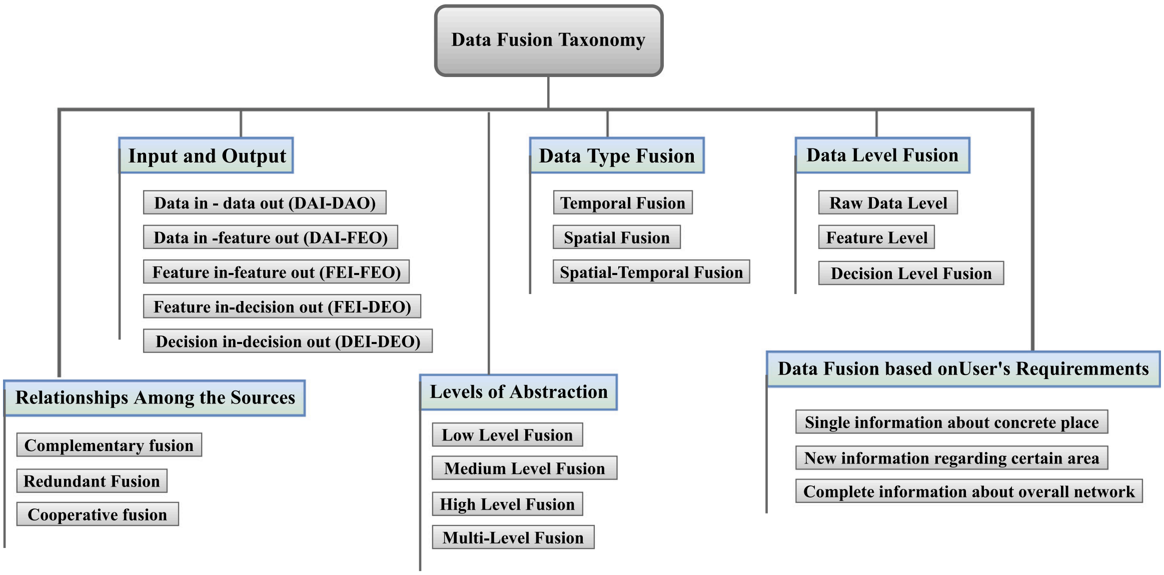


**Fig. 6.** Data fusion classifications based on different factors.

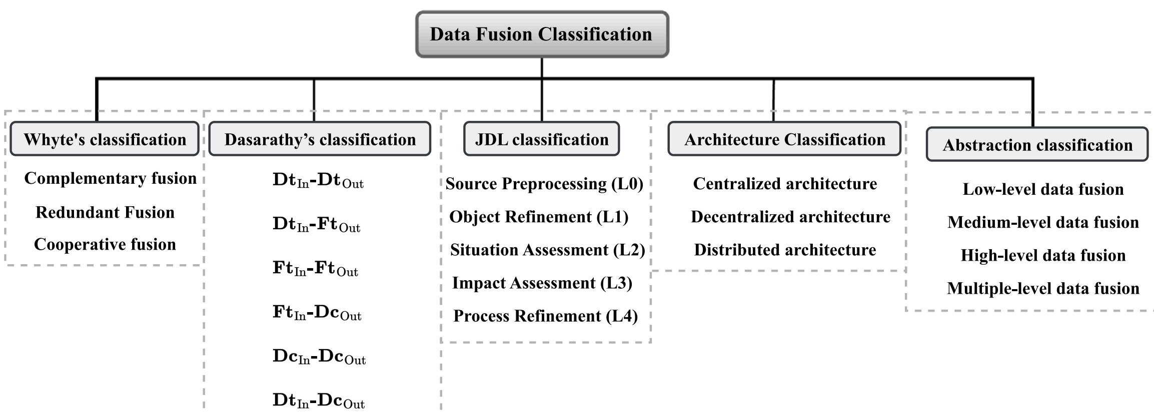


**Fig. 7.** Classifications of data fusion.

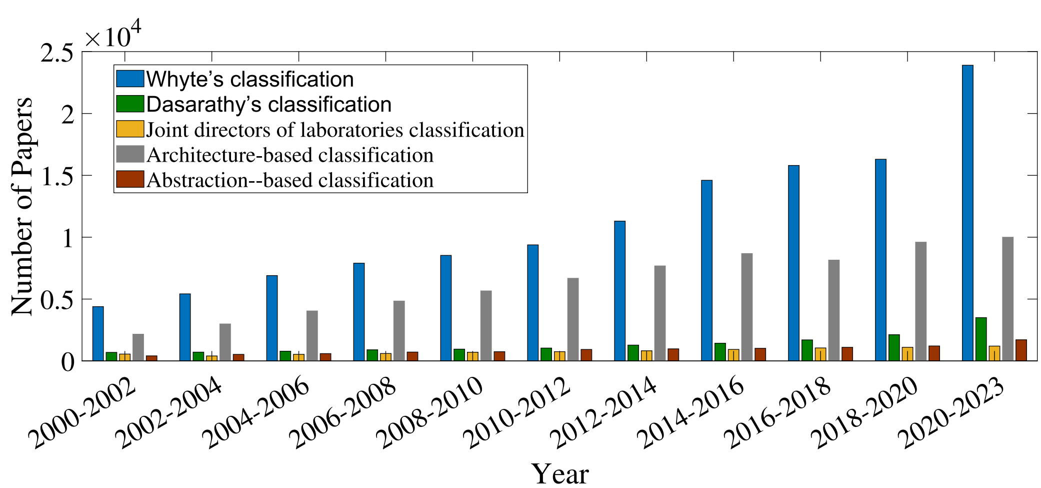


**Fig. 8.** Number of papers for all classifications.

– Surpassing Constraints for Enhanced Outcomes: Limitations or uncertainties in individual data sources can be overcome and the accuracy, robustness, or coverage of the fusion outcome can be improved. Complementary fusion is often used when the data sources capture different aspects or characteristics of the phenomenon of interest, and the fusion process aims at combining the data to obtain a more complete and accurate representation. As an example, assume

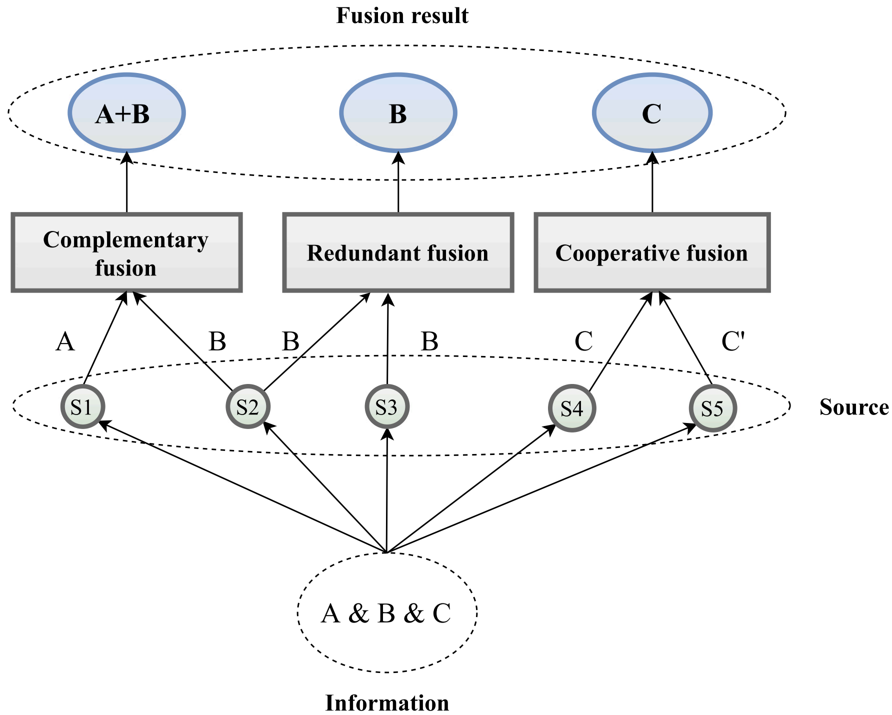


**Fig. 9.** Whyte's classification.

that an autonomous vehicle navigates through a complex urban environment. A number of sensors have been integrated into the vehicle, including cameras, LiDAR (Light Detection and Ranging), radar, and GPS. The sensors provide unique information about the surroundings; however, they also have some limitations. Despite the cameras' capability to capture rich visual details, they may struggle in low light conditions. Although LiDAR is capable of measuring distances with great accuracy, it might miss fine-grained textures. A radar is effective at detecting the speed of objects nearby, however, the spatial resolution of the radar is lower. While GPS provides global positioning, it may be imprecise in areas where satellite visibility is limited. By combining the outputs of these sensors, a more accurate perception of the environment can be achieved. In the fusion process, the complementary data streams are synthesized harmoniously with the aim of constructing a more precise and profound understanding of the phenomenon being monitored. As a result, this approach significantly enhances the autonomous vehicle's ability to make informed decisions and navigate safely through the complex urban environment.

– **Redundant fusion**: The concept of redundant fusion involves the combination of multiple sources of data that contain redundant information, with the goal of improving the reliability and robustness of the information obtained. As a result of redundant fusion, the same or similar information is gathered from multiple sources and integrated in order to reduce uncertainties, errors, and discrepancies that might arise from the individual data sources. As an example, Xue et al. [186] proposed a redundant fused microelectromechanical inertial measurement unit (MIMU) attitude system based on two stages of data fusion. By constructing a fused MIMU system in three dimensions and solving the problem of attitude quaternion with a Gauss–Newton algorithm, they achieved improved accuracy. The core characteristics of redundant fusion are summarized below:
  – Redundant data collection: In redundant fusion, multiple data sources capture redundant or overlapping information. The fusion process aims to combine or fuse the redundant data to improve the reliability or robustness of the fusion result.
  – Augmented precision and confidence: It can enhance the accuracy or confidence of the fusion outcome by combining multiple measurements or observations of the same phenomenon from different sources. This is achieved through the amalgamation of multiple measurements or observations of an identical phenomenon harvested from distinct origins. Consider multiple sensors that measure the same physical parameter. By virtue of their convergence, redundant sensors mitigate errors, uncertainties, and potential setbacks that are inherent in individual sources of data.
  – Enhanced holistic reliability and robustness: Through the principles of redundant fusion, the overarching dependability and fortitude of the fusion result are evidently improved. The remarkable improvement is achieved by strategically reducing reliance on a single data source, thereby seamlessly integrating data collected from a multitude of sources.
  – Improved reliability and robustness: Redundant fusion serves as a catalyst for augmenting the robustness and reliability of the fusion outcome. This is made possible by judiciously circumventing undue reliance on a solitary data source. Instead, it is integrated by judiciously integrating redundant data sourced from multiple independent origins.

– **Cooperative fusion**: Cooperative fusion, a prominent data fusion approach, involves the harmonious collaboration of multiple data sources or entities to improve the reliability, accuracy, and overall quality of the fusion outcome. In this method, all sensor information is combined to extract information that cannot be obtained through a single sensor. Cooperative fusion involves the active interaction and collaboration between these sources, as opposed to some other fusion techniques that focus on the passive combination of data from separate sensors. During cooperative fusion, the participating data sources exchange information, insights, and sometimes intermediate results, aiming to collectively refine the

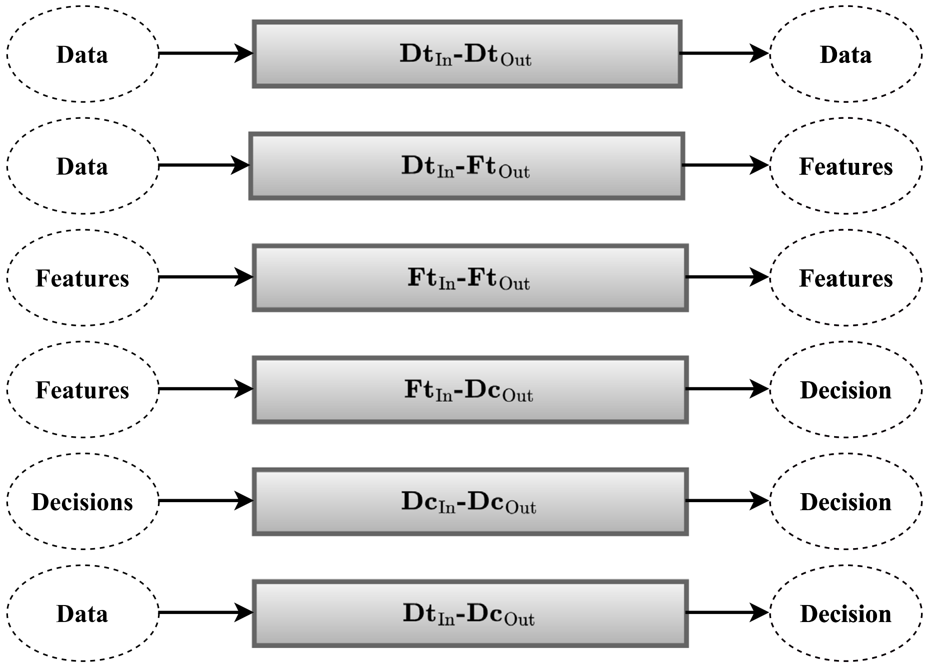


**Fig. 10.** Dasarathy's classification.

final result. By leveraging the strengths of each source while compensating for their limitations, the fusion system can utilize both their advantages and disadvantages. By working together as a team, the data sources are able to produce a more comprehensive and accurate understanding of the phenomena they are studying. As an example, Labayrade et al. [187] proposed a cooperative fusion approach between stereovision and laser scanners to take advantage of the best features and cope with the drawbacks of these two sensors to achieve robust, accurate, and real-time detection of multi-obstacles in the automotive industry. The following presents the main characteristics of this fusion type:

- Collaborative Interaction: In cooperative fusion, multiple data sources collaborate or cooperate to achieve a common goal or objective. The data sources exchange information, coordinate their actions, and work together as a team to improve the overall performance or efficiency of the fusion process.
- Distributed or Decentralized Dynamics: It can involve distributed or decentralized fusion techniques where the data sources communicate and cooperate in a peer-to-peer or networked manner. For example, in a wireless sensor network, sensors may collaborate to combine their data and obtain a consensus or a global view of the phenomenon being monitored.
- Centralized Coordination: Centralized fusion techniques can be involved where a central fusion node or agent coordinates the fusion process and receives data from multiple sources for fusion. The central node can make decisions based on the combined data or distribute fused data to other nodes for further processing.
- Unlocking Synergies: Cooperative fusion can enable synergistic effects among data sources, where the combined data or information from multiple sources is more valuable than the individual data from each source. The scalability, efficiency, and robustness of the fusion process can be improved by leveraging the collaboration and coordination among data sources.

### 3.1.2. Dasarathy's classification

Dasarathy's classification, also known as the information fusion taxonomy, is a widely used framework for categorizing data fusion techniques. It was proposed by Dasarathy [188], a renowned expert in the field of data fusion. He categorized fusion methods into five types based on the data input–output relation, as illustrated in Fig. 10. Generally, these five divisions can be referred to as:

- Data-level fusion: Data-level fusion involves combining raw data from multiple sources at the sensor or data acquisition level. This can include merging sensor measurements, sensor data alignment, aggregation, or registration. Data-level fusion techniques aim to improve the quality, completeness, or availability of the data used for further processing. Common methods used in data-level fusion include:
  - Averaging fusion: This method averages data from multiple sources to reduce noise and improve accuracy. It is especially effective when sources share similar characteristics and are subject to random variability.
  - Concatenation fusion: Raw data sequences are combined from different sensors into a longer sequence. When sensors measure the same phenomenon from different perspectives, this method is often used. Concatenation is commonly applied to data from imaging or spectroscopy sensors, allowing for a comprehensive analysis.
  - Weighted averaging: This technique operates in the same way as averaging but assigns different weights to different sources based on how reliable or accurate they are. It enhances the influence of reliable sources while reducing the impact of less reliable sources.
  - Bayesian fusion: Bayesian probability theory is used to integrate data and calculate the most probable outcome. This method takes into account prior knowledge and source reliability.
  - Dempster–Shafer theory: This theory deals with uncertainty by combining evidence from various sources using belief functions. It is especially useful when sources have varying degrees of reliability and uncertainty that need to be quantified.

- Kalman filtering: This method combines noisy measurements with predictions to provide accurate results. It is widely used for tracking applications involving continuous measurement sources.
- Particle filtering: A non-linear filtering technique that represents a probability distribution using particles. It is particularly useful in scenarios with complex dynamics and non-Gaussian uncertainty.
- Principal component analysis: Transforms data into a new space that captures the most significant variations, thereby reducing dimensionality. It is useful for identifying correlated or redundant information provided by different sources.
- Independent component analysis: Analyzes mixed signals and separates them into their independent source components. It is applied, when sources provide mixed or combined signals, and the goal, is to recover the original sources.
- Neural networks: These systems combine information from a variety of sources using artificial neural networks. They are particularly useful for analyzing complex patterns and relationships.
- Fuzzy logic fusion: This technique combines data using fuzzy logic principles to handle uncertainty. It is useful when sources provide incomplete or uncertain information.

• Feature-level fusion: Feature-level fusion involves combining extracted features or representations from the raw data of individual sources. This can include extracting relevant features or representations from each data source, such as image, audio, or text features, and combining them into a single feature vector or representation. Feature-level fusion techniques aim to capture relevant information from multiple sources and create a fused representation that can be used for subsequent processing. Common methods used in feature-level fusion include:

  - Feature concatenation: Features extracted from different sources are concatenated into a single vector. It is suitable when features are the same or dimensions are comparable.
  - Feature selection: Each source's relevant features are chosen based on their importance to the fusion process. Feature selection reduces the number of dimensions and eliminates redundant or less informative features. By enhancing efficiency and reducing noise, it improves the fusion process.
  - Principal component analysis: It transforms the original features into a new set of orthogonal features, called principal components. By capturing the maximum variance in the data, principal components can reduce the dimensionality of the data. It is effective at reducing high-dimensional data complexity and mitigating multicollinearity.
  - Wavelet transform: Highlights both low-frequency trends and high-frequency details of features by decomposing them into different frequency components. It is suitable for capturing localized patterns and variations that other methods may miss. It is useful in applications involving signal processing and image analysis.
  - Canonical correlation analysis: This technique determines linear relationships between features from different sources by finding canonical variables that have the greatest correlation. It is useful when features from different sources are correlated and need to be fused to capture common underlying patterns.
  - Independent component analysis: Aims to separate original features into statistically independent components. It is useful when sources provide mixed signals, and the goal is to determine which sources are independent.
  - Sparse coding: Sparse coding represents features as a sparse linear combination of learned dictionaries. It is effective when features can be sparsely represented, and compact representation is desired.
  - Fisher Vector Encoding: Providing a compact representation of feature distribution gradients. It is useful for visual feature fusion, such as image classification tasks.
  - Multiple kernel learning: Combination of multiple kernels (similarity functions) computed from different feature sources. It is beneficial when features from various sources have different characteristics and require separate similarity measures.

• Decision-level fusion: Decision-level fusion involves combining decisions or outputs obtained from individual sources to make a final decision or inference. This can include combining decisions obtained from different classifiers, decision-making algorithms, or decision rules. Decision-level fusion techniques aim to combine the outputs of different sources to improve the accuracy, reliability, or robustness of the final decision or inference. Standard methods used in decision-level fusion include:

  - Majority voting: Combining decisions from different sources is executed by selecting the decision that receives the majority of votes. It is particularly useful when sources have similar reliability and are prone to errors occasionally.
  - Weighted voting: This technique is similar to majority voting. Here, decisions are weighted differently depending on the reliability of the source. It enhances the influence of trustworthy sources and reduces the impact of less reliable ones.
  - Plurality voting: It is similar to majority voting, but the decision with the highest number of votes is chosen. It is suitable when there are multiple classes and no clear majority for a single class.
  - Expert opinion aggregate: Combines decisions from several experts, each with specialized knowledge. It considers a variety of perspectives to make better decisions.
  - Fusion by averaging: Numerical decisions from different sources are averaged to obtain a fused decision. It provides continuous or probabilistic outputs from sources.
  - Bayesian Model of Averaging: It combines decisions using Bayesian probability theory through posterior distribution calculation. It takes into account the reliability and uncertainty of each source's opinion.
  - Stacking: Combining the decisions of multiple classifiers with machine learning models. A meta-classifier learns to determine the final decision based on each individual classifier's output.
  - Logical Rules Fusion: Establishes logical rules for each source and combines these rules to arrive at a final decision. It is particularly useful when sources make decisions based on a variety of factors.
  - Consensus-based Fusion: Achieves consensus among sources by iteratively refining decisions until a consistent result is achieved. It is effective when sources provide conflicting information.
  - Evidence combination: Utilizes Dempster–Shafer's theory to combine decisions based on evidence and uncertainty. It is especially useful when information is uncertain or imprecise.
  - Game theory-based fusion: Analyzes interactions among sources to determine the best strategy for making a decision. It is useful when sources have conflicting motivations or interests.

**Table 9**
Overview and examples of Dasarathy's classification.

| Type | Input | Output | Analogue | Example |
|---|---|---|---|---|
| $Dt_{In}$–$Dt_{Out}$ | Data | Data | Data-level fusion | Fusion of multi-spectral data |
| $Dt_{In}$–$Ft_{Out}$ | Data | Features | Feature selection and feature extraction | Shape extraction |
| $Ft_{In}$–$Ft_{Out}$ | Features | Features | Feature-level fusion | Fusion of image and non-image data |
| $Ft_{In}$–$Dc_{Out}$ | Features | Decisions | Pattern recognition and pattern processing | Object recognition |
| $Dc_{In}$–$Dc_{Out}$ | Decisions | Decisions | Decision-level fusion | When sensors are not compatible |
| $Dt_{In}$–$Dc_{Out}$ | Data | Decision | Feature selection and pattern processing | Pattern recognition |

- Hybrid fusion: Hybrid fusion involves the combination of two or more of the above categories (data-level, feature-level, or decision-level fusion) in a hybrid manner. This can include combining data-level and feature-level fusion, feature-level and decision-level fusion, or data-level, feature-level, and decision-level fusion in a coordinated manner. Hybrid fusion techniques aim to leverage the strengths of different fusion approaches and can be tailored to specific applications or scenarios.

The different types of Dasarathy's classification are summarized in Table 9 and defined below:

- **$Dt_{In}$–$Dt_{Out}$**: A term used for a fusion type where both input and output are the raw data. Here, the goal is to refine and enhance raw data by combining information from different sources. The fusion process focuses on improving the accuracy, quality, and richness of the data itself. By amalgamating data from multiple sensors, this approach aims to create a more comprehensive and reliable dataset that captures a more complete perspective of the phenomenon being monitored. This type of fusion is particularly valuable when the raw data itself holds considerable value and insight.
- **$Dt_{In}$–$Ft_{Out}$**: In this type, the output is a set of features extracted from a set of raw data from multiple sensors as input. The main objective is to transform the raw input data into a more condensed and meaningful representation of features. These extracted features may consist of patterns, characteristics, or attributes that hold relevance for decision-making or processing later. By converting raw data into a feature-rich format, this type of fusion simplifies further analysis and allows efficient utilization of essential information.
- **$Dt_{In}$–$Dc_{Out}$**: Here, the output is a unique decision made directly from raw data obtained from multiple sensors as input. By bypassing the intermediate step of feature extraction, this approach intends to swiftly arrive at a decisive outcome. The fusion process distills the collective information from various sensors into a singular decision, which is essential for immediate actions. A fusion of this type is appropriate when the combined raw data directly informs a specific decision without any further processing or interpretation.
- **$Ft_{In}$–$Ft_{Out}$**: In this type, the input and output are both features. Some of the extracted features are fused to obtain a set of new features that is more information-dense. A key aspect of this approach lies in selecting and merging relevant features from the input to create a novel and enriched set of features in the outcome. Fusion creates a new feature representation that encapsulates the essential aspects of the input data by combining these selected features. An effective fusion occurs when the focus is on capturing the most relevant and informative attributes from various sources.
- **$Ft_{In}$–$Dc_{Out}$**: This type of fusion takes several features as input and generates a unique decision as output. Through the processing of input features, the fusion process culminates in a discerning and definitive decision. The goal is to harness the collective information contained in the input features to guide a conclusive result. An important advantage of this approach is the ability to use the features gathered from different sources directly to inform a decision without involving complicated analysis or interpretation.
- **$Dc_{In}$–$Dc_{Out}$**: Here, multiple and often contradictory decisions are used as input to provide a unique and reliable decision as output. The significance lies in resolving conflicting or divergent decisions from different sources to arrive at a unified and dependable result. Fusion is particularly important when combining inputs from different decision-makers or models in order to generate a coherent decision that takes all viewpoints into account.

Dasarathy's classification provides a systematic framework for categorizing data fusion techniques based on the level of processing performed on the data. It has been widely used in the field of data fusion and has served as a foundation for many research studies and applications. Researchers and practitioners often refer to Dasarathy's classification to categorize and compare different data fusion techniques based on their level of processing, which can help in selecting appropriate strategies for specific applications and evaluating their effectiveness. The choice of data fusion category depends on the particular application requirements, the available data sources, and the desired outcomes. An appropriate fusion technique should be selected based on the problem's context, as each category has its strengths and limitations. With the advancement of artificial intelligence and machine learning, more advanced fusion techniques have been developed, including deep learning-based fusion and graph-based fusion, which do not directly fit into Dasarathy's original classification but can still be classified based on the degree of processing of the data. In the following sections, we will explain how to combine ML with data fusion.

#### 3.1.3. Joint directors of laboratories classification

The Joint Directors of Laboratories (JDL) classification is the prime conceptual pattern in data fusion architectures. The American Department of Defence (DoD) collaborated with JDL to initially propose the concept in 1986 [189]. They categorized the data fusion processing flow into five basic levels connected by an information bus and sources, as illustrated in Fig. 11. The five processing levels are defined as follows:

- **Source pre-processing (L0)**: The lowest data fusion level, also known as the source processing level or L0, fuses data at the raw data level. Examples of information fused at this level are data fusion for signals, pixel fusion for images, and extracted data fusion for text sources. Source pre-processing is meant to maintain useful information for high-level functions. This level ensures that raw data is calibrated, aligned, and standardized. By maintaining the integrity of useful information from a variety of sources, it prepares it for higher-level processing. As an example of these models, in a weather forecasting system, raw data from

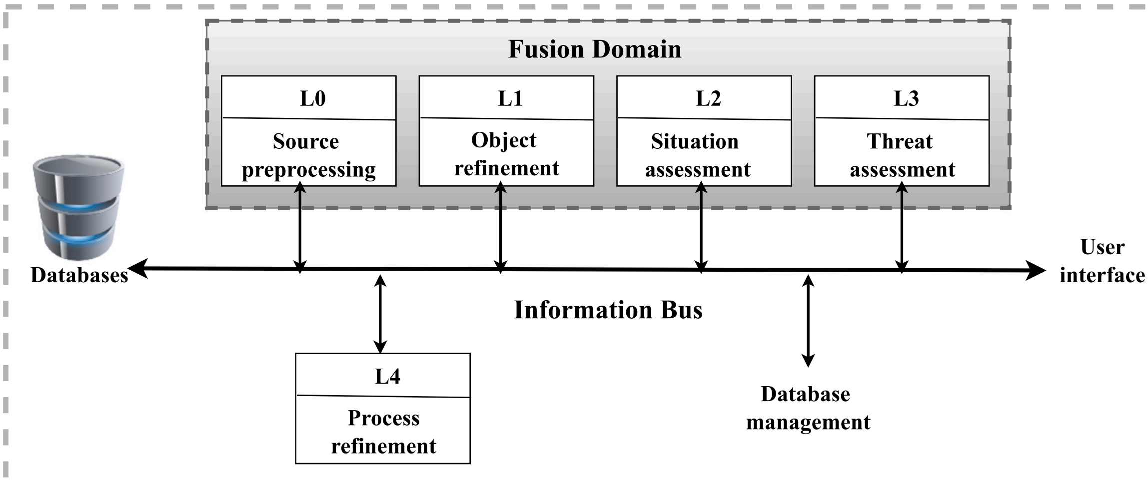


**Fig. 11.** The JDL data fusion framework.

various weather stations, satellites, and sensors are fused at the L0 level. This includes data on temperature, humidity, wind speed, and atmospheric pressure. Source pre-processing ensures data alignment, calibration, and standardization before further analysis.

– **Object refinement (L1)**: This level further processes the extracted information from L0. The standard procedures of this level include Spatio-temporal alignment, correlation, association, clustering or grouping methods, removing false positives, state estimation, identity fusion, and fusing features extracted from multimodal data sources (such as images). The outputs of this stage are object discrimination, i.e., identification and classification, and object tracking, i.e., the state and orientation of an object. The overall aim of this level is to enhance the structure of the input data to increase information consistency. By filtering out noise and false positives, L1 enhances the quality of data. It involves techniques like object tracking, state estimation, and feature extraction, leading to a more accurate and coherent representation of the detected objects. As an example of these models, in a surveillance system, video feeds from different cameras are fused at the L1 level. The system employs object tracking algorithms to refine the raw video data into identified objects (people, vehicles, etc.). False positives are removed, and the system estimates the speed and trajectory of each object.
– **Situation assessment (L2)**: This stage aims to step up the level of inference of level 1. Situation assessment focuses on establishing relationships between observed events to identify likely situations. This level assigns values to relations such as proximity and communication to specify the importance of the entities in a particular environment. The final result of this level is a set of high-level abstractions. This level focuses on understanding the relationships and interactions between objects or entities. It provides insights into higher-level abstractions and patterns, leading to a better understanding of the overall situation. As an example of these models, consider a smart city system that fuses data from traffic cameras, environmental sensors, and public transportation. At the L2 level, the system identifies patterns and relationships in the data, determining factors like traffic congestion, pollution levels, and public transport availability. This allows for an assessment of the overall urban environment.
– **Impact Assessment (L3)**: In this level, the impact of the activities identified in L2 is evaluated to achieve a practical view of the system's state. Therefore, after assessing the current condition, a future projection is inferred to recognize possible risks, vulnerabilities, and operational opportunities. In other words, this stage aims to evaluate the risk or threat and predict the possible results. L3 evaluates the potential consequences of detected events, allowing for predictive insights and risk assessment. It aids in understanding the implications of different scenarios and facilitating informed decision-making. As an example of these models, in a healthcare system, patient data from various sources like wearable devices and medical records are fused at the L3 level. The system evaluates the patient's current health status and predicts potential health risks based on historical data. This enables healthcare professionals to take preventative measures.
– **Process Refinement (L4)**: This stage aims to improve the processes from levels 0 to 3 and manage resources and sensors. Thus, the objective is to obtain efficient resource management while taking care of scheduling, task priorities, and controlling present resources. This level focuses on optimizing the fusion process itself, managing resources, and improving efficiency. In addition, it ensures that resources are allocated effectively and the fusion process is continually improved. As an example of these models, in a manufacturing plant, data from sensors across different machines are fused at the L4 level. The system optimizes the manufacturing process by analyzing the data to adjust production schedules, allocate resources efficiently, and ensure minimal maintenance downtime.

The original JDL model mainly focuses on data fusion issues. However, with the advent of big data, machine analytics, and cloud computing technologies, there is an ever-increasing need to integrate people and machines. As a result, the JDL model has been revisited to address these gaps [189,190].

#### *3.1.4. Architecture-based classification*

An architecture-based classification is a classification approach used in data fusion or sensor fusion. Here, the classification is based on the architecture or structure of the system or network used for the fusion. In architecture-based classification, the organization and arrangement of sensors or data sources, and the processing and integration methods used are considered. Further aspects include the hierarchical structure of sensors, the connectivity and communication patterns among sensors, the fusion algorithm employed, and the overall system design. The architecture or structure of the data fusion system can significantly influence the fusion process's performance, efficiency, and robustness.

The three main types of architecture-based classification are illustrated in Fig. 12 and defined as follows:

– **Centralized architecture**: In this scheme, the fusion node residing in a central processor obtains data from all input sources to conduct the fusion process.

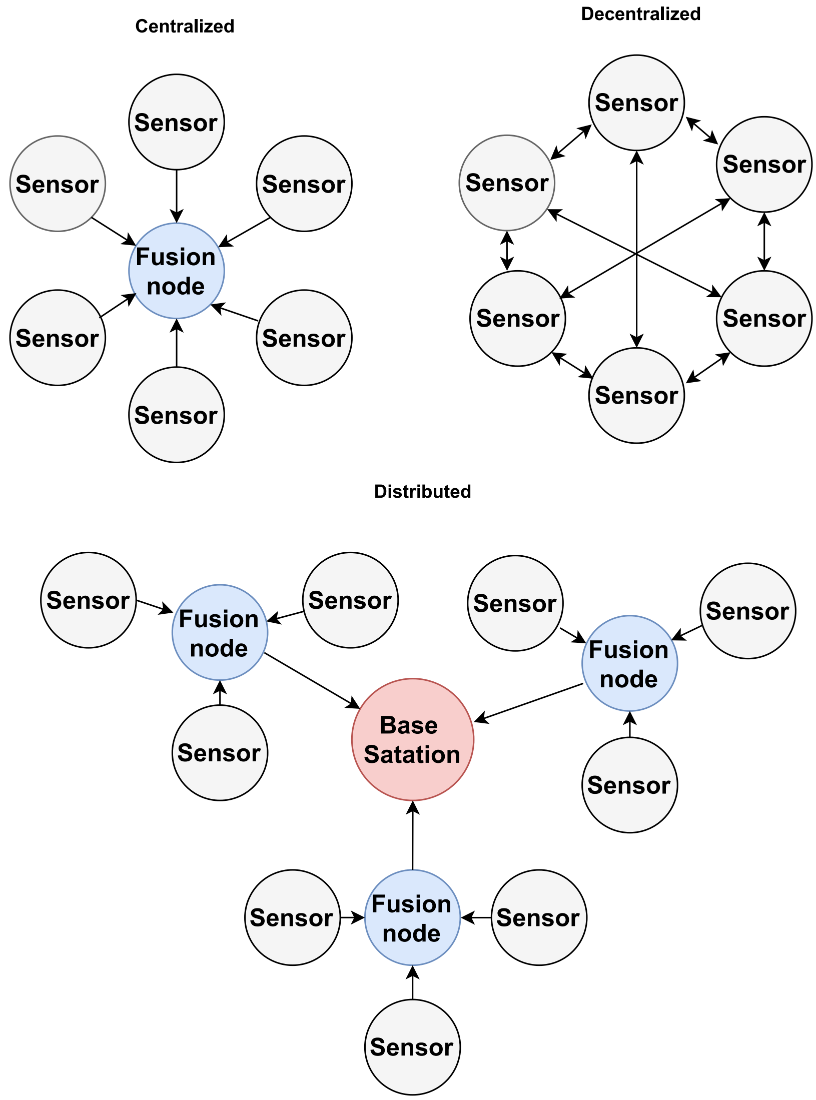


**Fig. 12.** Classification of data fusion techniques based on the type of architecture (centralized, decentralized, and distributed architecture).

– **Decentralized architecture**: This approach comprises a group of nodes where each node has its own processing abilities. Hence, data fusion is conducted at each node using local data obtained from neighboring nodes. Data fusion based on a decentralized architecture typically communicates data using the Shannon Entropy and Fisher information criteria as opposed to the object's state.
– **Distributed architecture**: In this scheme, measurements from each node are first locally processed at a fusion node and then sent to the base station. These processes include data association and state estimation. The fusion node accounts for the data received from neighboring nodes. Thus, each fusion node provides its local view over the member state, which is used as an input to the fusion flow to attain the final global decision about the system state.

The following describes different architecture-based classification approaches and provides examples:

1. Centralized architectures involve a central processing unit that receives data from multiple sources and performs the fusion process. This architecture is suitable for scenarios where a single entity has complete control over the data fusion process and real-time decision-making is not critical. The key characteristics of centralized architectures include:

• Data Collection: Various sources of data are transmitted to a central processing unit. The central unit acts as a central repository for incoming data.
• Fusion Process: To combine and analyze the received data, the central processing unit employs fusion algorithms. Techniques such as statistical methods, machine learning, or expert systems can be used.
• Decision-Making: Following the completion of data fusion, the central unit generates decisions or outputs based on the data merged. Reports could be produced, patterns identified, or predictions made.

The benefits of centralized architectures include; Holistic View: All incoming data is accessible to the central processing unit, which allows for a comprehensive understanding of the situation; Sophisticated Fusion: Due to the centralized nature of data, complex fusion techniques can be employed. It is possible to analyze more data simultaneously, which leads to more accurate and detailed results; Resource Allocation: The data processing can be made more efficient by concentrating resources, such as computational power and memory, in the central unit.
It is used in a wide range of fields. For meteorology, various weather stations and satellite sources send information to a central weather prediction center. For a specific region, the data

is fused to generate accurate weather forecasts. As an example, in the financial sector, a central analytics unit can fuse data from various markets, stocks, and economic indicators in order to predict and provide insight into investment decisions. Hospitals can fuse patient data from various sources, including electronic health records and medical devices, to provide a comprehensive picture of a patient's condition.

2. Decentralized architectures allow data sources to process their data locally and make decisions based on their own fused information. This architecture is often used in scenarios where multiple entities have autonomy and must make decisions independently based on their local information. For instance, in a distributed sensor network for structural health monitoring, each sensor node may have its fusion algorithm to process locally collected data and make decisions about the structure's health. The key characteristics include:

    - Local Processing: Data sources in a decentralized architecture are capable of processing their collected data locally. The process involves performing initial fusion steps and generating insights using its own data.
    - Autonomous Decision-Making: Using locally fused information, decentralized systems allow each data source to make independent decisions. By doing so, entities are empowered to make decisions tailored to their own specific contexts rather than relying on a central authority. Communication: In spite of the fact that data sources operate independently, communication among them might occur in order to share insights, collaborate, or exchange fused data as needed.

    The benefits of decentralized architectures are: Reduced Latency: Local processing eliminates the need to transmit data to a central hub, providing faster decision-making in real-time applications; Data Privacy: Since data is processed locally, sensitive information does not have to be transmitted to a central unit, enhancing data privacy and security; and Scalability: Decentralization supports systems with numerous sources, allowing them to be scalable for applications such as sensor networks.

    Decentralized architecture is used in a wide range of fields. As part of a smart home environment, IoT devices, such as thermostats and smart locks, process their data locally to make decisions, reducing the need to communicate constantly with a central hub. For a city-wide traffic management system, traffic cameras and sensors can locally analyze traffic data so that signal timing can be optimized, and congestion can be managed without the need for a central server. For precision agriculture, farmers can analyze soil conditions, moisture levels, and nutrient content locally by placing sensors on their crops, allowing them to make real-time decisions without central intervention.

3. Hierarchical architectures involve multiple levels of data fusion, where data from different sources are first fused at lower levels. Then the fused information is further fused at higher levels to make decisions. This architecture is useful when different levels of data fusion are required to handle different levels of complexity or uncertainty in the data. For example, in a military surveillance system, data from various sensors may be first fused at a local level, and then the fused information is further fused at a higher level to obtain a more comprehensive situational awareness. There are a number of key characteristics including:

    - Multi-Level Processing: There are multiple levels in this architecture, each responsible for a specific function. Each of these levels represents an increased level of abstraction and complexity in the processing of data.
    - Information Flow: In order to extract fundamental insights or features from data, lower levels of fusion are first applied. At higher levels, more sophisticated analysis and decision-making are carried out based on the fused information from lower levels.
    - Layered Refinement: As the hierarchy progresses, the quality of information progressively refines and improves. The process continues as the data moves through the hierarchy, producing increasingly valuable insights.

    The benefits of hierarchical architecture include: Adaptability: Different levels of data granularity can be handled by this architecture, and it can accommodate different types of data sources and complexities; Specialization: The hierarchy can be divided into levels according to the type of data being analyzed, allowing for optimal decision-making at each level of the hierarchy; Holistic Understanding: Multi-level understanding ensures a comprehensive understanding by combining insights from different levels to provide a more accurate and informed assessment.

    The application of this architecture is wide-ranging. For self-driving cars, multiple sensors such as cameras, LiDARs, and radars are fused to provide information to the controller. During lower levels of processing, raw sensor data is processed, while higher levels integrate this information in order to understand the vehicle's environment and provide safe navigation. In a health monitoring system, data from electronic health records, wearable devices, and sensors is merged in a hierarchical way. Vital signs are processed at the lower levels, while higher levels integrate this information to assess a patient holistically. For military surveillance, information from a variety of sensors, such as drones, satellites, and ground-based sensors, is merged hierarchically. At the initial level, raw sensor data is processed, and at higher levels, the information is combined to create a comprehensive situational awareness.

4. Distributed architectures involve data fusion across multiple nodes or entities in a network. Each node has its own data sources and fusion algorithm, and the fusion process occurs locally at each node. The fused information may be exchanged among the nodes for further processing or decision-making. This architecture is commonly used in scenarios where data sources are geographically distributed and real-time or near real-time decision-making is required. For example, in a collaborative sensing network for environmental monitoring, data from multiple sensors distributed in a region may be fused locally at each sensor node and then exchanged among the nodes for global decision-making. Key characteristics include:

    - Decentralized Processing: Nodes in distributed architectures independently process their own data locally using their fusion techniques. The reduction of central coordination is achieved through localized processing.
    - Collaborative Fusion: A fusion process is collaboratively implemented by communicating and exchanging information between nodes. For further processing or decision-making, the combined information from one node can be shared with others.
    - Network Interaction: Efficiencies in communication between nodes are essential to the success of the architecture. The exchange of data, synchronization, and collaboration between nodes are essential to the success of distributed fusion.

    The benefits of distributed architecture are: Real-Time Decision-Making: By processing data locally and sharing relevant insights among nodes, distributed architectures facilitate real-time or near-real-time decision-making; Robustness: By reducing the impact of node failures or communication breakdowns on the overall fusion process, the distributed nature enhances system robustness; Scalability: This architecture is scalable, which makes it suitable for applications involving many data sources.

It has different applications. For environmental monitoring, sensor nodes communicate wirelessly with one another to collect data about the environment. Data from the nodes is fused collaboratively to provide a holistic picture of the environment. Across a power grid, distributed meters and sensors gather information about grid conditions and electricity consumption. Using local fusion, each node is able to monitor and coordinate its power distribution in real-time. In a distributed traffic surveillance system, different cameras at different intersections process traffic data locally and share insights with neighboring cameras, improving traffic management collectively.

5. Layered architectures involve data fusion at different layers or levels, each with a specific function or task. The fused information from one layer may be used as input for the next layer, and the process continues until a final decision or output is obtained. This architecture is commonly used in complex systems where different levels of information need to be combined for decision-making. For example, in a healthcare system, data from multiple sources, such as electronic health records, wearable devices, and medical sensors, may be fused at different layers to obtain a comprehensive patient assessment. Key characteristics include:

   - Sequential Processing: In layered architectures, data is processed in a step-wise manner through different layers. Each layer is responsible for specific tasks and processes before passing the refined information to the next layer.
   - Progressive Refinement: Information is refined and enriched as it moves through the layers. The fusion process builds upon the insights generated at previous layers, resulting in more comprehensive and informed outcomes.
   - Task-Specific Layers: Each layer addresses a specific aspect of data fusion, including feature extraction, pattern recognition, and decision-making. In the end, the decision is based on the contributions of the specialized layers.

   The benefits of this model are: In-depth Analysis: Layered architectures allow for in-depth analysis of data at different levels, contributing to a more comprehensive understanding of the phenomenon; Progressive Enhancement: By refining data through each layer, the architecture ensures that fused information becomes more accurate and valuable with each subsequent step; Complex Systems: Layered architectures are suitable for complex systems where multiple levels of data processing are necessary to capture the nuances of the data.

   The architecture can be applied to a variety of fields. For image processing, layered architectures may include initial layers that recognize edges and shapes, followed by intermediate layers that recognize specific objects or patterns. In medical diagnosis, layered architectures can combine data from patient histories, medical images, and electronic health records. In the initial layers, data may be processed independently, and in subsequent layers, this information is integrated to provide a comprehensive diagnosis. In environmental sensing, layered architectures can process data from various sensors to monitor factors such as humidity, temperature, and pollution levels. A holistic understanding of the environment is achieved through the refinement of the data at each layer.

6. Network topology-based classification considers how the data sources are connected or organized in the system. Examples of network topologies include star, tree, mesh, and ring topologies, among others. The network topology can affect the communication, data exchange, and fusion process among the data sources. For example, in a wireless sensor network, a star topology may involve one central node that collects data from multiple sensor nodes, while a mesh topology may apply direct communication among all sensor nodes. Key Characteristics include:

   - Communication Structure: The topology of a network specifies how the nodes (data sources) and communication links are arranged. Data sources exchange information and collaborate differently depending on the network topology.
   - Data Exchange: Data exchange, sharing, and fusion among data sources depends on the network topology. Communication paths and information flow in a network are determined by the topology.
   - Impact on Fusion: Communication efficiency, data transmission delays, redundancy, fault tolerance, and overall data fusion performance are all affected by network topology.

   Several benefits can be derived from this architecture, including: Communication Efficiency: Highly optimized network topologies are capable of improving data exchange efficiency, reducing latency, and improving overall communication efficiency; Redundancy and Reliability: Mesh and tree topologies can contribute to fault tolerance and redundancy in networks, ensuring reliable data exchange even in case of node failures; Scalability: Different network topologies can accommodate different numbers of data sources, making them suitable for various applications.

Each architecture has its own advantages and limitations, and the choice of architecture must be selected based on specific application requirements, available resources, and desired performance metrics.

*3.1.5. Abstraction–based classification*

An abstraction-based classification is a classification approach used in various domains such as machine learning, natural language processing, and image recognition. It involves using abstraction or generalization techniques to extract higher-level features or representations from data, which are then used for classification or categorization tasks. Abstraction-based classification techniques aim to simplify the complexity of data by extracting relevant abstract features that capture the underlying patterns or characteristics of the data.

In data fusion, this classification type typically involves using feature extraction, feature selection, or dimensionality reduction techniques to transform the fused data into a set of abstract features that capture the relevant information from multiple sources. These abstract features can be used as input for classification algorithms to perform tasks such as target recognition, anomaly detection, or decision-making. For example, in SHM, where data from multiple sensors or sources are fused to assess the health condition of a structure, abstraction-based classification techniques can be used to extract abstract features from the fused sensor data, such as vibration patterns, strain distributions, or modal parameters. These abstract features can then be used to classify the health condition of the structure, such as normal, damaged, or deteriorated, using classification algorithms.

Abstraction-based classification in data fusion can also be applied in other domains, such as remote sensing, environmental monitoring, or medical diagnosis, where data from multiple sources must be combined and analyzed for decision-making purposes. For example, in remote sensing, data from multiple sensors such as optical, thermal, and radar can be fused using abstraction-based classification techniques to extract abstract features that represent the land cover, vegetation health, or water quality. These abstract features can be used for classification tasks such as land use mapping, vegetation classification, or water pollution assessment.

The choice of abstraction-based classification techniques in data fusion depends on the nature of the data, the specific application, and the desired classification performance. Common techniques include feature

**Table 10**
Characteristics of the three basic abstraction levels (low, medium and high) and multi-level data fusion.

| Level | Type | Bandwidth | Characteristics | Ref. |
|---|---|---|---|---|
| Low-level | Raw data level fusion | High, very high | – Superior detection performance<br>– Requires accurate data transformation<br>– Transformation errors have a direct impact on its performance<br>– Computationally expensive | Li et al. [193], Li and Wang [194], Kulkarni and Rege [195], Muhammad et al. [196], Solanky and Katiyar [197] |
| Medium-level | Feature level fusion | Moderate | – Relies on a sensor independent detection capability<br>– Extracted features are combined in common decision space<br>– Classification is optimized for specific targets | Goshvarpour and Goshvarpour [198], Kannan et al. [199], Cai et al. [200], Jeng and Chen [201] , Sun et al. [202] |
| High-level | Decision level fusion | Low, very low | –Relies on independent detection capability in each sensor<br>– Decisions are combined based on AND/OR Boolean or Bayesian inference<br>– Computationally simplest | Lip and Ramli [203], Castanedo [204], Sinha et al. [205], Bala et al. [206] |
| Multi-level | Multi-level fusion | High, very high, moderate | – Balances the trade-off between different levels of fusion | Zhao et al. [207], Song et al. [208] |

extraction methods such as statistical measures, wavelet transforms, and deep learning-based feature extraction; feature selection methods such as information gain, mutual information, or genetic algorithms; and dimensionality reduction methods such as Principal Component Analysis (PCA), Singular Value Decomposition (SVD), and t-Distributed Stochastic Neighbor Embedding (t-SNE).

Floridi [191] defined four levels of abstraction as follows:

– **Low-level data fusion**: Often termed raw data fusion, employs the raw data as input. The benefits include deriving more accurate information, such as higher SNR, compared with using sources individually.
– **Medium-level data fusion**: Also known as feature-level fusion, it aims to fuse characteristics such as shapes, textures, and positions to obtain components that enhance decision-making.
– **High-level data fusion**: This type, also defined as decision-level data fusion, fuses symbolic representations of sources for a more accurate final decision.
– **Multiple-level data fusion**: Here, information from the different basic types of abstractions described above is processed. For example, Hydra is a multi-level data fusion framework used in different applications such as agriculture [192].

Fig. 13 provides an overview of two classes of data fusion, namely single-level and multi-level fusion, each of which is classified into different types of data fusion. Various levels of data fusion have their advantages, disadvantages, and application domains. Characteristics and related reference studies of the three basic abstraction levels and multi-level data fusion are presented in Table 10. Typically, features are obtained by fusing the original information, and decisions are made by applying several fusions. Multi-level fusion has extensively been addressed in the literature. For example, Hydra is a data fusion application composed of three layers of data fusion [192]. The different types of abstraction data fusion levels are often categorized into two groups, (1) data fusion level based on supervised learning and (2) data fusion level based on unsupervised learning. Below, the three basic levels of abstraction-based data fusion are discussed in more detail.

• Raw data level fusion
Raw data level fusion is the lowest level of data fusion and processes the raw information directly captured by the sensors. The outcome is high reliability, and accuracy and contains less noise. Raw data level fusion models are used for different schemes: signal fusion [209,210], image fusion [211,212], and other similar scenarios. Below, the advantages and disadvantages of raw data level fusion are summarized:

  – **Advantages**: Original data fusion preserves more details about the system that may not be discovered in other fusion levels.
  – **Disadvantages**: Poor performance in real-time applications; needs a reliable fault-tolerant ability to cope with uncertainty; heavy computation load and instability of sensor information itself.

The implementation of raw data level fusion involves the utilization of various techniques to enhance the accuracy, reliability, and usefulness of the collected data. Below we summarize some of the commonly employed techniques:

  – Kalman Filter Method [213,214]: This estimation technique combines measurements and predictions to determine the state of the system more accurately and reliably. It is particularly beneficial when measurements are noisy and uncertain.
  – Weighted Average Method [215,216]: In this technique, individual sensor measurements are assigned specific weights based on their reliability and quality. By combining these measurements appropriately, it is possible to provide a more accurate representation of the phenomenon.
  – Election Decision Method [217]: Based on certain criteria, the election decision method chooses the most suitable source or sensor. It can be useful when multiple sources provide data, necessitating a decision about the trustworthiness of a source.
  – Mathematical Statistics Method [218]: This category encompasses a range of statistical techniques used in data analysis and interpretation. In order to achieve more accurate fusion results, these methods can be used to identify patterns, trends, and relationships in raw data.

For interested readers, Table 11 shows the different raw data fusions with related references.

• Feature level fusion
Inputs to this level of fusion are extracted features from recorded data. The outputs are advanced features or characteristics of other patterns that facilitate decision-making. Data derived from this process is more comprehensive and polished to show different information attributes compared with the raw-data level fusion. Below, the advantages and disadvantages of feature-level fusion are addressed:

  – **Advantages**: The reduced amount of processed information improves the real-time performance of the model.

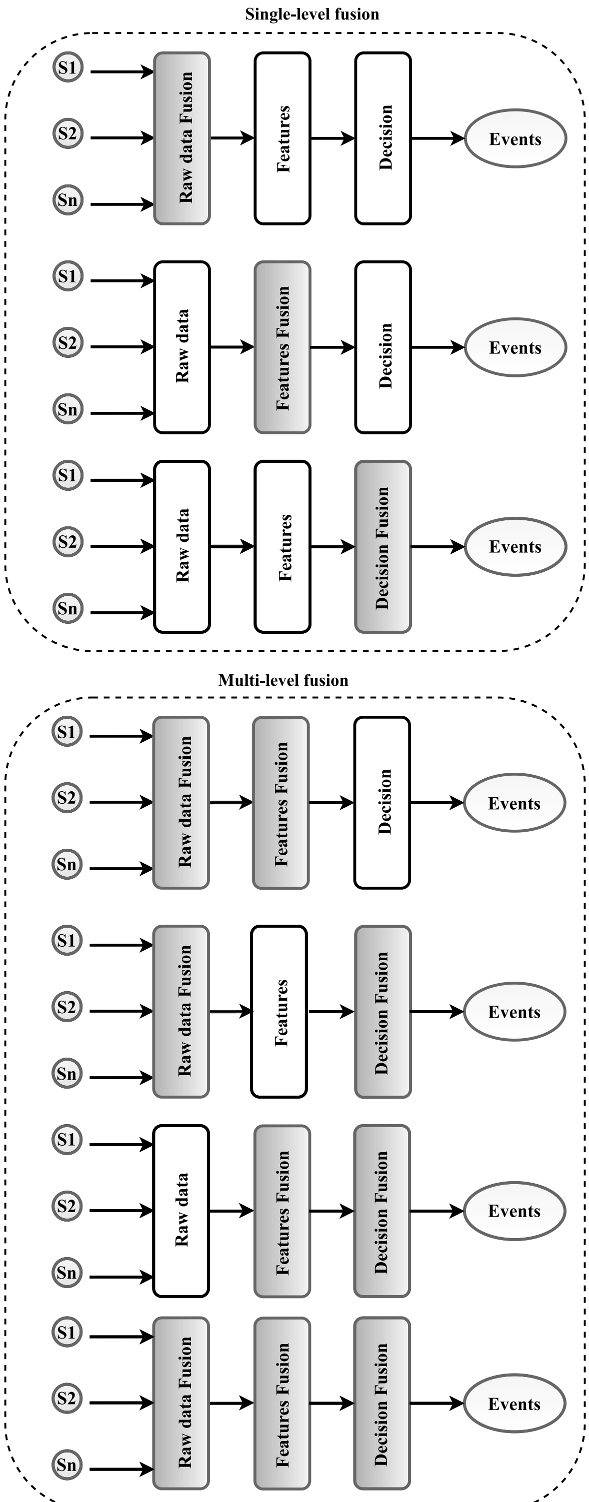


**Fig. 13.** Classification based on data level fusion.

– **Disadvantages**: Its precision is often worse than raw-data level fusion.

The process of feature-level fusion employs a variety of methods to improve decision-making and information extraction. Several techniques utilized for feature-level fusion are listed below:

**Table 11**
Different raw data level fusion methods.

| Methods | Refs |
| --- | --- |
| Cluster analysis | Li et al. [219], Di Vita et al. [220] |
| Classical inference | Candy [221], Blakely and Pethel [222] |
| Bayesian inference | Qin et al. [223], Hara et al. [224] |
| Dempster–Shafer | Çavdar et al. [225], Cuzzocrea et al. [226] |
| Neural networks | Li et al. [227], Uddin et al. [228] |
| Fuzzy logic | Liu et al. [229], Talhaoui et al. [230] |
| Estimation theory | Mahmoud et al. [231], Mahmoud et al. [231] |
| Entropy | Mukherjee et al. [232], Hao et al. [233] |

– Fuzzy Inference [234,235]: A versatile method used for handling uncertainty by representing information that is vague or imprecise. It is especially effective in situations where there are no well-defined boundaries between categories.
– Kalman Filter [236,237]: Kalman filters have traditionally been applied to raw data fusion, but they can also be used at the feature level to refine and enhance extracted information. In this method, noise and uncertainty are mitigated by using the principles of prediction and correction to iteratively refine the estimated features.
– Neural Network [238–240]: Neural networks, especially deep learning architectures, have received significant attention because they can learn intricate patterns and representations from data. Through feature-level fusion, neural networks can combine information from multiple sources to extract high-level features. Some commonly used feature-level fusion techniques employed by neural networks are:

  ∗ Transformer-based Architectures: Originally designed for natural language processing, transformer architectures can be used for feature fusion across many different domains. Consequently, these architectures, including BERT, GPT, and their variants, are highly effective at fusing information from various sources, as they use self-attention mechanisms to capture contextual relationships between features.
  ∗ Graph Neural Networks (GNNs): These networks are designed to process graph-based data, making them ideal for fusion tasks involving relationships between features. A GNN propagates information through graph structures, which allows them to capture the complex interactions among features from a variety of sources.
  ∗ Multi-Modal Fusion Networks: These networks combine features from a variety of modalities, such as images and text. Advanced architectures are employed in these networks for the efficient processing of diverse data types and the extraction of meaningful relationships between the data types.
  ∗ Contrastive Learning: This type of learning is designed to bring similar instances closer together and dissimilar instances apart in a space of learned features. This technique has gained popularity as a method for combining features from different sources by training the network to distinguish between them while merging features with similar characteristics.
  ∗ Hybrid Architectures: In hybrid architectures, multiple neural network paradigms are combined for feature fusion. An example is the use of CNNs for image features and recurrent neural networks (RNNs) for sequential data features to improve fusion results.
  ∗ Cross-Attention Mechanisms: These mechanisms capture relationships between features from different sources in addition to self-attention mechanisms. While considering the interactions between sources, the network can focus on the most relevant information.

**Table 12**
Different fusion methods at feature level.

| Methods | Refs |
|---|---|
| Cluster analysis | Sundareswaran et al. [242], Zhou et al. [243] |
| Bayesian inference | Echeveste et al. [244], Nouri and Toufigh [245] |
| Dempster–Shafer theory | Li et al. [246], Sarkar et al. [247] |
| Kalman Filter | Lee et al. [236], Wang et al. [237] |
| Production Rule | Wang et al. [241] |
| Neural networks | Ji et al. [248], Chen and Chen [249] |

  * Transfer Learning with Pre-trained Models: This technique uses pre-trained models on large datasets that are later fine-tuned for specific feature fusion tasks. These models have learned rich representations from diverse sources of data, making them adaptable and effective for fine-tuning and feature fusion.
  * Generative Adversarial Networks (GANs): These networks are used to generate synthetic features that bridge the gap between different types of data. GANs learn to fuse features that capture shared and complementary information by training the network to produce features that are consistent with multiple sources.
  * Meta-Learning: The concept of meta-learning allows neural networks to learn new tasks quickly from limited data sets. Networks can learn how to effectively combine features from different sources using minimal labeled data by applying meta-learning to feature fusion.

- Production Rule [241]: The production rule system is a set of conditional statements (rules) used for guidance in making decisions based on specific conditions. By leveraging these rules, features extracted from different sources are integrated in a systematic and rule-based manner.

The techniques mainly exploited for feature-level fusion include fuzzy inference [234,235], Kalman filter [236,237], neural network [238,239], and production rule [241]. Table 12 lists several fusion methods at the feature level.

• Decision level fusion
As the highest level of data fusion, techniques aim to fuse decisions based on features generated in preceding stages to reach a unique conclusion. Therefore, this level of fusion aggregates clashing decisions to reach a final decision about the system state. Table 13 presents the most common decision-level combination methods divided into soft and hard combination types. The advantages and disadvantages of decision-level data fusion are summarized as follows:

- **Advantages**: There are several advantages such as high flexibility, good fault tolerance, small communication bandwidth requirements, and strong anti-interference capability.
- **Disadvantages**: Decision-level fusion requires data compression of measured sensor data, which results in the loss of details and involves high processing costs.

Techniques at this level mainly include the D-S evidence method [250,251] and the Bayesian method [252,253], which are both aimed at inferring a final decision based on clashing evidence. Table 14 lists several fusion methods at the decision level.

In Table 15, we review recent research studies that apply different types of data fusion methods for SHM.

## 4. Multimodal data fusion

When multiple sensors share or duplicate information obtained from the same source, redundant fusion occurs, as deciphered by Durrant-Whyte [184]. This challenge is more problematic when dealing with redundancy in the information presented by multimodal data sources such as images. In this case, the main question is whether an automated fusion strategy can be devised to extract the maximum information from the image sources. Bramon et al. [281] addressed this question by developing a strategy based on mutual information (MI). It is known that MI can quantify the amount of information shared between two data sources. Accordingly, the fused image is constructed based on the source images' most informative unit of graphic information (voxels). As such, the most informative matched voxels (from each pair) are selected to construct the fused data set with the highest specific information.

When two registered images are considered with $N$ voxels integrated into a common model, the three basic components of the channel $X \to Y$ can be presented as follows:

1. **The input distribution** $p(x)$: It is defined as $p(x) = \frac{n(x)}{N}$, where $n(x)$ is the number of voxels in bin $x$.
2. **The output distribution** $p(Y)$: It represents the normalized frequency of each bin $y$ as $p(y) = \sum_{x \in X} p(x)\, p(y|x) = \frac{N(y)}{N}$ where $n(y)$ indicates the number of voxels concerning bin $y$.
3. **The conditional probability matrix** $p(Y|X)$: It is defined as $p(Y|X) = \frac{n(x,y)}{n(X)}$, where $n(x, y)$ indicates the number of voxels in image $X$ presenting intensity $x$ such that the corresponding voxel in $Y$ presents the intensity $y$.

Given the above definitions, three following concepts are defined:

1. **Surprise** ($I_1$): It is defined as follows:
$$I_1(x;Y) = \sum_{y \in Y} p(y|x)\, log\, \frac{p(y|x)}{p(y)} \tag{1}$$
where $I_1(x;Y)$ indicates the surprise about $Y$ from occurring $x$.
2. **Predictability** $I_2$: It is defined as follows:
$$I_2(x;Y) = -\sum_{y \in Y} p(y)\, log\, p(y) + \sum_{y \in Y} p(y|x)\, log\, p(y|x) \tag{2}$$
where $I_2(x;Y)$ indicates the uncertainty change about $Y$ once $x$ occurs.
3. **Entanglement** ($I_3$): It is defined as:
$$I_3(x;Y) = \sum_{y \in Y} p(y|x)\, I_2(y;X) \tag{3}$$
where a large value indicates that the most informative input values $x$ are those associated with the most informative outputs $y$.

Two different fusion methods, Symmetric and Asymmetric, were proposed based on the defined measures $I_1$, $I_2$, and $I_3$. The formulas of both methods are presented in Table 16.

Recently, Malawade et al. [282] developed a multimodal data fusion algorithm, called HydraFusion, that fuses data captured from a camera, radar, and lidar sensors to maximize robustness while maintaining efficiency in the performance of autonomous vehicles (AVs). The Python code for HydraFusion can be found in https://github.com/AICPS/hydrafusion.

## 5. Traditional data fusion techniques

Over the years, numerous mathematical theories have been applied to develop data fusion algorithms. Meng et al. [17] presented a comprehensive introduction and discussion of these techniques. Here, an overview is given covering the most popular data fusion techniques.

**Table 13**
Most common decision-level combination methods.

| Type | Bandwidth | Method | Description | Refs. |
|---|---|---|---|---|
| Hard | Very low | – Boolean<br>– Weighted Sum Score<br>– M-of-N | – Apply AND, OR logical operators to combine clashing evidence (decisions)<br>– Assign weights to the decisions made by sensors through inverting the covariance matrix and summing the derived score functions<br>– Make a final decision based on m-out-of-n agreeing on sensors' decisions | Arora and Mahajan [254], Nallagonda et al. [255] |
| Soft | Low | – Bayesian<br>– Dempster–Shafer<br>– Fuzzy Variable | – Apply the Bayes rule to aggregate conditional probabilities of sensors' independent decisions<br>– Apply the D-S decision rule to combine belief functions constructed based on sensors data<br>– Apply fuzzy logic to combine variables obtained from combined membership functions | Soltane and Mimen [256], Yan et al. [257] |

**Table 14**
Different fusion methods at decision level.

| Methods | Refs |
|---|---|
| Classical inference | Taraldsen and Lindquist [258], Shen et al. [259] |
| Bayesian inference | Martinez-Hernandez and Dehghani-Sanij [260], Changqiang et al. [261] |
| Dempster–Shafer theory | Mokarram et al. [262], Hamid et al. [263] |
| Neural networks | Shahid et al. [264], Fuentes-Alvarez et al. [265] |
| Fuzzy logic | Kaczorek and Jacyna [266], Tarannum and Jabin [267] |
| Generalized evidence | Liu et al. [268], Deng [269] |
| Processing theory | Zhu et al. [270], Joseph and Gaba [271] |

**Table 15**
A review of recent studies using abstraction-based data fusion strategies for SHM.

| Method | Num. | Exp. | Description | Ref. |
|---|---|---|---|---|
| Raw-data Level Fusion | ✓ | ✓ | This paper proposes a new strategy for fusing the signals from multiple ultrasonic sensors to identify cracks in reinforced concrete using non-decimate discrete wavelet transforms. | Chakraborty and Stolinski [272] |
| Decision Level Fusion | ✓ | ✓ | This study proposes a multi-level decision fusion strategy that balances the value of information (VoI) with the SHM's intended function. | Sharif Khodaei and Aliabadi [273] |
| Decision Level Fusion | ✓ | ✓ | This paper proposes an SHM framework based on hybrid intelligent systems and decision-level analysis to compute composite structure health indicators. | Sun et al. [274] |
| Feature Level Fusion | ✓ | ✓ | Based on the feature fusion technique and hybrid deep learning architecture, a novel approach for SHM is developed to improve detection performance with low computational cost and storage requirements. | Dang et al. [275] |
| Decision Level Fusion | ✓ | ✓ | This study shows the effectiveness of the decision-level fusion of multi-vibration signals for damage detection. The damage detection accuracy of the employed convolutional neural network (CNN) improved significantly. | Zhang et al. [276] |
| Decision Level Fusion | ✓ | ✓ | This study presents a multi-sensory damage detection strategy to process high-dimensional Lamb-wave signals to achieve high-accuracy damage identification results. | Mishra et al. [61] |
| Decision Level Fusion | ✓ | ✓ | Using a decision-level fusion strategy and a one-dimensional convolutional neural network (1-D CNN), this paper proposes a novel strategy to improve SHM accuracy significantly. | Teng et al. [277] |
| Feature Level Fusion | ✓ | | This article presents a hybrid dense sensor network that combines capacitive-based thin film sensors with fiber Bragg grating sensors to measure additive strain over large regions. | Downey et al. [278] |
| Feature Level Fusion | ✓ | ✓ | Canonical correlation analysis (CCA) is employed for feature level fusion of two feature types, peak to peak amplitude from ultrasonic measurements and strain measured by strain gauges, for damage detection in concrete structures. | Chakraborty et al. [279] |
| Raw-data Level Fusion | ✓ | ✓ | This work proposes a robust method for developing uni-directional strain maps from a novel large-area electronic additive strain signal. The device is known as a soft elastomeric capacitor (SEC). | Sadoughi et al. [280] |

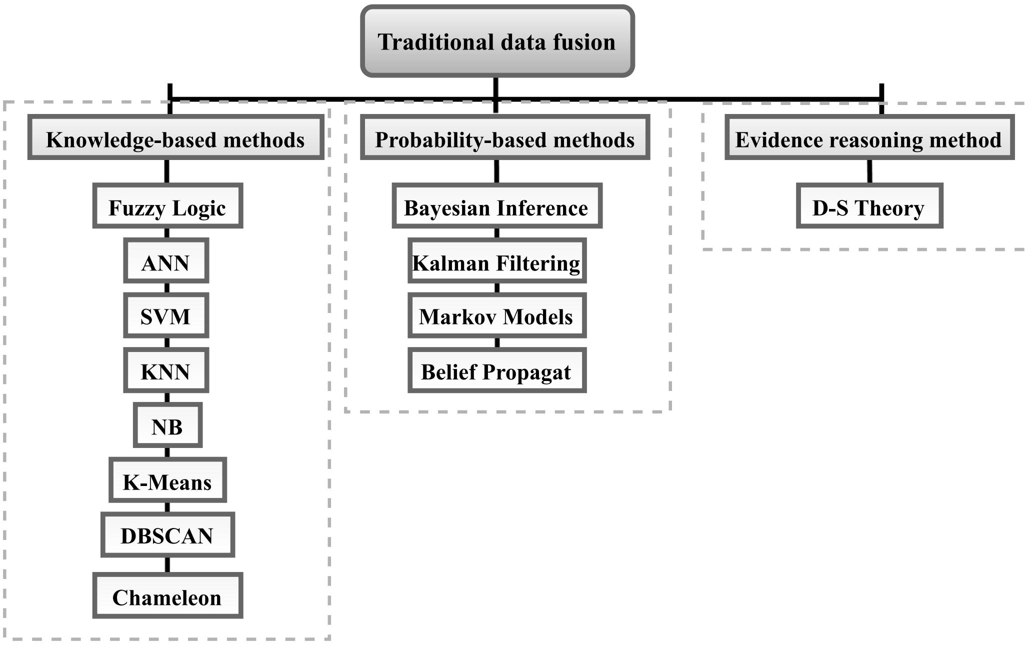


**Fig. 14.** Traditional data fusion methods.

**Table 16**
Data fusion methods for multimodal images.

| Symmetric method | |
|---|---|
| Type | Formula |
| $I_1$ fusion | $z = \begin{cases} x, & I_1(x;Y) > I_1(y;X) \\ y, & otherwise, \end{cases}$ |
| $I_2$ fusion | $z = \begin{cases} x, & I_2(x;Y) > I_2(y;X) \\ y, & otherwise, \end{cases}$ |
| $I_3$ fusion | $z = \begin{cases} x, & I_3(x;Y) > I_3(y;X) \\ y, & otherwise, \end{cases}$ |
| Asymmetric method | |
| $z = \begin{cases} x, & I_2(x;Y) > I_3(x;Y) \\ y, & otherwise, \end{cases}$ | |

Specific characteristics, challenges, benefits, and shortcomings are summarized for their application in SHM systems. According to Pires et al. [283], most traditional data fusion techniques can be categorized into (1) probability-based methods, (2) evidence reasoning methods, and (3) knowledge-based methods. Fig. 14 illustrates this categorization presenting associated data fusion methods. Below, the advantages and disadvantages of these methods are summarized.

- **Probability-based methods (PBM)**:
  - Advantages: The model estimation allows an unsupervised classification.
  - Disadvantages: Prior knowledge is required on the inferior probability of the data set.
  - Level of Fusion: Low, Medium.
  - Example applications in SHM: Liu et al. [284], Wang et al. [285].
- **Evidence reasoning methods (EBM)**:
  - Advantages: It assigns an uncertainty level to each data source.
  - Disadvantages: A degree of evidence for each concept is assigned.
  - Level of Fusion: High.
  - Example applications in SHM: Sun et al. [286], Sousa et al. [287].
- **Knowledge-based methods (KBM)**:
  - Advantages: Easy to implement, robust to noise, includes imprecision and uncertainty, and has strong learning ability.
  - Disadvantages: The intervention of a human expert is required, lack of data transparency, and difficult to determine the size of hidden layers.
  - Level of Fusion: Medium, High.
  - Example applications in SHM: Khoa et al. [288], Wang et al. [289].

The following sections provide background information and concepts related to each of the presented types of traditional data fusion. In Table 17, we present a review of recent papers applying traditional data fusion methods in SHM.

### *5.1. Probability-based methods*

In probability-based methods, the density function or probability distribution is introduced to deal with information imperfection, which indicates the random variables' dependency and specifies the relationship between various data sets. The three basic classical probability-based theories that can be used for data fusion are Maximum Entropy (ME), Bayesian (BAYES), and Maximum Likelihood (ML) approach [294]. Below, the theoretical base for developing a probabilistic data fusion model is presented.

#### *5.1.1. Fusion of homogeneous data*

Suppose two different views of the same data $x$ are given as $y$ and $z$. These can be two different images from two angles from an object situation. The aim is to update the situation $x$, given two different versions of it, i.e. $y = \phi(x)$ and $z = \psi(x)$. Thereby, the objective is to find a better unique presentation of $x$.

Adopting the independence assumption for the two sets of data, the Bayes can be written as follows:

$$p(x|y,z) = \frac{p(y,z|x)\ p(x)}{p(y,z)} = \frac{p(y|x)\ p(z|x)\ p(x)}{p(y,z)} \tag{4}$$

**Table 17**
Applications of traditional data fusion techniques in structural system identification.

| Methods | Num. | Exp. | Description | Ref. |
|---|---|---|---|---|
| Probability-based methods | ✓ | | This paper presents two fusion methods based on an arithmetically weighted average and a geometrically weighted average to reconstruct probabilistic damage images. | Li et al. [290] |
| Probability-based methods | ✓ | | This work presents an SHM system based on Acousto Ultrasonics (AU) to inspect a full-scale Door Surround Structure (DSS). | Moix-Bonet et al. [291] |
| Probability-based methods | ✓ | ✓ | This study develops an improved probability-based diagnostic imaging (PDI) strategy with corrected weight distribution to enhance the accuracy of damage localization. | Liu et al. [292] |
| Knowledge-based method | ✓ | ✓ | This work presents a two-stage knowledge-based DL algorithm to detect real-time automated damage using augmented reality smart glasses. | Wang et al. [289] |
| Evidence reasoning method | ✓ | ✓ | This work proposes a strategy based on the information fusion method to improve damage detection accuracy and stability of a building structure. | Zhou et al. [293] |
| Evidence reasoning method | ✓ | ✓ | This paper addresses the condition monitoring of cable-stayed bridges by developing a multilevel assessment framework. The framework synthetically combines the evaluation results from field monitoring, numerical simulations, and visual inspection. | Sun et al. [286] |

The main challenge is to assign the probability $p(y|x)$, $p(z|x)$, and particularly $p(x)$. Let us assign a Gaussian distribution to each of the aforementioned probabilities. Also, assume the mean and variance of $x$ to be known as $\mu$ and $\sigma^2$, respectively. Likewise, the variance of $p(y|x)$ and $p(z|x)$ is $\sigma_1^2$ and $\sigma_2^2$. The posterior probability $p(x|y,z)$ involves all the information about $x$ and, therefore, can be used to make any inference on $x$, such as the point estimator. This process can be described as follows:

Let us take $\theta = (\mu, \sigma^2, \sigma_1^2, \sigma_2^2)$. Then, the following probability theories can be used to make a point-estimator inference on $x$:

- Maximum *a posteriori* (MAP):

$$\hat{x} = \arg\max_{x}\{p(x|y,z;\theta)\} \tag{5}$$

- Posterior Mean (MP):

$$\hat{x} = \mathrm{E}(x|y,z;\theta) = \int x\ p(x|y,z;\theta)\ \mathrm{d}x \tag{6}$$

- Marginal Posterior Modes (MPM):

$$\hat{x} = \arg\max_{x_i}\{p(x_i|y,z;\theta)\} \tag{7}$$

where

$$p(x_i|y,z;\theta) = \int p(x|y,z;\theta)\ \mathrm{d}x_1\ \mathrm{d}x_2 \dots \mathrm{d}x_n \tag{8}$$

Two challenges are faced in practice, these are:

1. Specifying the probability laws $p(y|x)$, $p(z|x)$, and particularly $p(x)$.
2. Determining the parameters $\theta = (\mu, \sigma^2, \sigma_1^2, \sigma_2^2)$.

*5.1.2. Fusion of heterogeneous data*

Suppose two different kinds of data are available. The aim is to reconstruct a tomographic image by integrating X-ray and ultrasonic testing data. The X-ray measures the mass density of the matter ($x$) in a data set $x'$, and the ultrasonic testing probes the acoustic reflectivity of the matter ($r$) in a data set $r'$. Obviously, $x'$ and $r'$ represent the shifted versions of $x$ and $r$, respectively, as $x' = \phi(x)$ and $r' = \psi(r)$. For simplicity, we assume that $\phi()$ and $\psi()$ are both linear functions. Adopting the independence assumption for the two sets of data, the Bayes can be written as follows:

$$p(x,r|x',r') = \frac{p(x',r'|x,r)\ p(x,r)}{p(x',r')} = \frac{p(x'|x)\ p(r'|r)\ p(x,r)}{p(x',r')} \tag{9}$$

where

$$p(x',r') = \iint p(x'|x)\ p(r'|r)\ p(x,r)\ \mathrm{d}r\ \mathrm{d}x \tag{10}$$

Likewise, to the previous case, a problem arises from the unknown probability laws $p(x'|x)$, $p(r'|r)$, and $p(x,r)$. If a mathematical relationship between r and $x$ can be found, this problem can be converted to the homogeneous data fusion problem. Therefore, the problem requires an assumption for this relationship. The readers are referred to [294] for further details.

Probability-based methods include state–space models [295], Bayesian inference [296], Markov models [297], possibility theory [298], evidential reasoning [299], and least square-based estimation methods [300] such as optimal theory [301], Kalman filtering [302], and regularization and uncertainty ellipsoids [303]. The limitations of probabilistic fusion algorithms include:

– It can be challenging to define prior probabilities and specify a density function.
– Probability-based methods are limited in terms of dealing with complex multivariate information.
– These methods cannot handle uncertainty.

Below, we summarize the advantages and disadvantages of the most popular probability-based methods and provide application examples other than SHM.

- Bayesian Inference
  - Advantages: Efficient, simple, and good at identifying prior knowledge.
  - Disadvantages: Requires a prior probability, can be highly complex when dealing with multivariate information and a large amount of detailed information; bad at dealing with uncertainty.
  - Other applications: Traffic anomaly [304] and activity recognition [305].
- Kalman Filtering
  - Advantages: Easy to implement, simple, optimal in the sense of mean-squared error.
  - Disadvantages: Linear format when assuming zero-mean Gaussian noise, sensitive to outliers' corruption.
  - Other applications: Real-time management of traffic system [306].
- Markov Models
  - Advantages: Accurate prediction.
  - Disadvantages: Not suitable for long-term prediction.
  - Other applications: Appliance control [307].

**Table 18**
Recent papers using probability-based methods applied to SHM systems.

| Methods | Num. | Exp. | Description | Ref. |
|---|---|---|---|---|
| Bayesian Inference | ✓ | | This paper develops a finite mixture modeling method based on the sequential quadratic programming algorithm to formulate the joint probability density function of wind speed and direction based on the wind monitoring data of a bridge structure. | Ye et al. [309] |
| Bayesian Inference | ✓ | | This paper addresses a long-term (over one year) variation and statistical analysis of data captured from the SHM system of a suspension bridge. | Li et al. [310] |
| Kalman Filtering | ✓ | ✓ | This work employs an extended Kalman filter (EKF) to develop an online model for the fatigue life prediction of a structure. | Kuncham et al. [311] |
| Kalman Filtering | ✓ | ✓ | This paper presents a methodology based on a multi-rate Kalman Filter (KF) to fuse data from temperature and strain sensors to overcome the impact of temperature on the tracking accuracy of a structural member's Neutral Axis (NA). | Soman et al. [312] |
| Markov Models | ✓ | ✓ | This work proposes a hidden Markov modeling-based framework via acoustic emission (AE) measurements to monitor corrosion faults in prestressed concrete materials. | Dubuc et al. [313] |
| Belief Propagate | ✓ | | This work presents a novel parallel implementation technology based on the belief propagate method using a graphics processing unit (GPU) device for wave-based SHM of laminated composite plates. | Zuo et al. [314] |

- Belief Propagate
  - Advantages: Can deal with massive amounts of information.
  - Disadvantages: Falls easily in loops, and convergence is difficult to achieve when dealing with nonlinear information.
  - Other applications: State estimation [308].

In Table 18, we review some recent papers based on the probability-based methods used in SHM systems.

### 5.2. Evidence reasoning methods

Dempster–Shafer's (D–S) evidence theory is the most commonly applied evidence reasoning method. It aims to aggregate beliefs from new evidence and can overcome ignorance stemming from a lack of data. The following sections provide basic background information on the D-S theory and application procedures for decision-making.

#### 5.2.1. Frame of discernment

The frame of discernment is composed of $M$ mutually exhaustive and exclusive hypotheses as follows:

$$\Theta = \{\theta_1, \theta_2, \dots, \theta_M\} \tag{11}$$

The uncertainties in the D-S theory are represented by probability assignments to the space $\Theta$, analog to the classical probability theory. However, an important difference exists: The D-S theory involves assigning a probability to any subset of $\Theta$. The power set $2^\Theta$ is thus defined as follows:

$$2^\Theta = \{\emptyset, \{\theta_1\}, \{\theta_2\}, \dots, \Theta\} \tag{12}$$

where $\emptyset$ represents the empty set. The following are the properties of the power set $2^\Theta$:

1. The number of its elements is equal to $2^M$.
2. Any subset of the set $2^\Theta$, excluding possible singleton of values, i.e. their union. For example, $\{\theta_1, \theta_2, \theta_3\} = \theta_1 \cup \theta_2 \cup \theta_3$.
3. The basic probability assignment (BPA) assigns the complete probability to the power set $2^\Theta$.

#### 5.2.2. Mass function

The mass function $M : s^\Theta \rightarrow [0, 1]$ exhibits the following properties:

$$m(\emptyset) = 0 \tag{13}$$

and

$$\sum_{\forall\theta\in 2^\Theta} m(\theta) = 1 \tag{14}$$

#### 5.2.3. D-S rule of combination

Information acquired from a network of multiple independent sensors represents the evidence required by the D-S theory. The data fusion practice leverages normalization to simplify and summarize the acquired information by highlighting the agreement among multiple sources and discarding all conflicting evidence.

The D-S theory defines the combination rule of two evidence $m_1$ and $m_2$, also known as joint mass, as follows:

$$m_{1,2}(A) = \frac{1}{1-K} \sum_{B\cap C = A \neq \emptyset} m_1(B).m_2(C) \tag{15}$$

where (15) conforms to both commutative and associative laws, $K$ represents the degree of conflict between two sources of evidence and is obtained as follows:

$$K = \sum_{B\cap C=\emptyset} m_1(B).m_2(C) \tag{16}$$

In Eq. (15), $\frac{1}{1-K}$ is a normalization factor that facilitates aggregation via ignoring the conflicting evidence. The following summarizes the advantages and disadvantages of the D-S theory and presents application examples other than SHM.

- D-S Theory
  - Advantages: Can deal with information assignment and complementary hypotheses, and can solve uncertainty problems.
  - Disadvantages: Difficult to specify mass functions.
  - Other applications: Fire detection [315]; occupancy sensing [247]; activity recognition [316].

In Table 19, we review some recent papers based on the evidence reasoning method in SHM systems.

**Table 19**
Recent papers using the evidence reasoning approach for SHM systems.

| Methods | Num. | Exp. | Description | Ref. |
|---|---|---|---|---|
| D-S Theory | ✓ | | This paper presents a D-S evidence theory-based approach using the change ratio of modal strain energy to enhance the accuracy of damage identification. | Zhao and Zhang [317] |
| D–S Theory | ✓ | | This paper presents a novel strategy to fuse a multi-sensory nondestructive testing data set consisting of ultrasonic pulse-echo, impact-echo, and ground penetrating radar data measured on a large-scale concrete specimen with built-in honeycombing defects. | Völker and Shokouhi [318] |
| D–S Theory | ✓ | | This work presents a fusion approach based on the D–S theory for optimum damage detection in structural applications in the case of multiple damage locations and three-dimensional systems. | Grande and Imbimbo [319] |
| D-S Theory | ✓ | ✓ | This paper proposes an intelligent detection method to improve machine learning and data mining performance for structural damage identification of buildings. | Zhou et al. [293] |
| D-S Theory | ✓ | ✓ | This work proposes using the D-S theory to account for the associated uncertainty in the procedure of producing distribution maps. | Niamir et al. [320] |

### *5.3. Knowledge-based method*

Knowledge-based methods can enable the fusion center to obtain information from large sets of inaccurate data. Furthermore, it does not require a density/distribution function. The following are key characteristics of knowledge-based methods:

- Incorporation of Expert Knowledge: This method incorporates expert knowledge or rules derived from domain experts who have a thorough understanding of the problem. The expertise of these specialists can prove invaluable for steering the fusion process and providing context-specific knowledge.
- Semantic Interpretation: This method takes information beyond raw data by considering its semantics. The fusion results can be more informative as they consider the meaning, relationships, and context of the data.
- Uncertainty Handling: Uncertainties can be managed with expert knowledge. It is possible to improve the reliability of fusion outcomes by incorporating domain-specific uncertainty models or rules, especially when the data is incomplete or noisy.
- Rule-based Fusion: This approach involves defining a set of rules that dictate how fusion should be performed based on certain conditions. The fusion process can be guided by these rules in capturing relationships between various sources of information.
- Contextual Considerations: These methods consider the context in which the fusion is occurring. Factors such as the environment, task requirements, and user preferences are taken into account to make better fusion decisions.
- Human–Machine Collaboration: The collaboration of humans and machines is often necessary for this type of method. Fusion is guided by human input, while technical aspects of information integration are handled by automated algorithms.

Knowledge-based techniques include intelligent aggregation techniques [331], fuzzy logic [332], and machine learning [333]. Machine learning can be categorized into three groups:

- Supervised Learning [334]: Examples are K-Nearest Neighbor (KNN), Naive Bayes (NB), Support Vector Machines (SVM), and Artificial Neural networks (ANN).
- Unsupervised Learning [335]: Examples are Density-Based Spatial Clustering of Applications with Noise (DB- SCAN), Chameleon, and K-Means.
- Semi-supervised Learning [336]: An example is Transductive Support Vector Machine (TSVM) [337].

Below, the benefits and shortcomings of knowledge-based methods are summarized and application examples other than SHM are presented.

- Fuzzy Logic
  - Advantages: Ability to deal with inaccurate and uncertain information.
  - Disadvantages: Difficult to set up rules and membership functions.
  - Other applications: Fall detection [338].
- ANN
  - Advantages: Accurate prediction, robust techniques for non-linear data fusion.
  - Disadvantages: Training process requires different features; unable to explain decisions, high computation cost.
  - Other applications: Crowd flows forecasting [339].
- SVM
  - Advantages: Efficient with massive data sets and high dimensional information.
  - Disadvantages: Processing capacity for big data sets is poor and sensitive to inadequate information.
  - Other applications: Vehicle localization [340].
- KNN
  - Advantages: Simple model, fast model generation.
  - Disadvantages: Slow prediction, inability to process biased data sets, and data sets with many features.
  - Other applications: Parking spot detection [341].
- NB
  - Advantages: Fast training, uncomplicated, applicable to high-dimensional data sets, easy prediction from the trained model.
  - Disadvantages: Cannot utilize attribute-related data sets.
  - Other applications: Activity recognition [342].
- K-Means
  - Advantages: Easy implementation, simple model.
  - Disadvantages: Requires a threshold setting strategy, prone to errors due to the presence of outliers and noise.
  - Other applications: Data injection detection [343].
- Density-Based Spatial Clustering of Applications with Noise (DB-SCAN)

**Table 20**
Review some recent papers in knowledge-based method.

| Methods | Num. | Exp. | Description | Ref. |
|---|---|---|---|---|
| Fuzzy Logic | ✓ | | This article introduces a new Fuzzy Krill Herd hybrid approach based on online responses to identify the overall structural integrity of an in-service bridge. | Jahan et al. [321] |
| Fuzzy Logic | ✓ | ✓ | This article combines a Fuzzy Logic System (FLS) and Empirical Wavelet Transform (EWT) to identify and localize early bearing degradation considering different working conditions. | Gougam et al. [322] |
| ANN | ✓ | ✓ | This study presents a novel artificial intelligence-based SHM strategy using neural network modeling to fuse recorded data for reliable monitoring. | Chang et al. [323] |
| ANN | ✓ | ✓ | This paper presents a data mining-based damage identification method based on ANN-based data fusion to localize/quantify multiple damage cases from the modal analysis of intact and damaged slab-on-girder bridges. | Gordan et al. [324] |
| SVM | ✓ | | This paper presents a strategy based on SVM employed to identify the proposed nonlinear baseline model using the fusion of features extracted from hysteresis loop analysis (HLA). | Zhou et al. [325] |
| SVM | ✓ | ✓ | This paper proposes an acquisition function-based version of the Bayesian optimization (BO) method to optimally tune the hyperparameters of the soft margin SVM for SHM. | Agrawal and Chakraborty [326] |
| KNN | ✓ | ✓ | This article employs a one-class kNN rule termed AMSD-kNN and adaptive Mahalanobis-squared distance for structural condition monitoring under EOCs. | Sarmadi and Karamodin [327] |
| KNN | ✓ | | This paper presents a kNN-based strategy for localization and quantifying bridge damage using the time-varying natural frequencies due to varying operational conditions (i.e., moving truck). | Feng et al. [328] |
| K-Means | ✓ | | This paper presents a Piezoelectric lead zirconate titanate (PZT) sensor-based self-diagnosis approach using ANN and K-means clustering analysis. | Jiang et al. [329] |
| DBSCAN | ✓ | ✓ | This paper presents a strategy based on the joint exploitation of satellite radar remote sensing measurements and AI techniques to preliminarily identify and rank possible critical constructions in a built environment. | Mele et al. [330] |

  – Advantages: Able to identify the noise source, capable of spatial clustering of any data shape, high clustering speed.
  – Disadvantages: When density is uneven, clustering quality is poor.
  – Other applications: Noise cancellation [344].

- Chameleon:
  – Advantages: No need for a preset number of clusters.
  – Disadvantages: Massive calculation and thus significant storage needs.
  – Other applications: Data injection detection [345].

In Table 20, we review recent papers based on the knowledge-based method in SHM systems.

**Table 21**
Deep learning architectures, types, and applications.

| Architecture | Type | Application |
|---|---|---|
| Discriminative | Supervised | Customer support [349] |
| Generative | Unsupervised | |
| Hybrid | Semi-supervised | Smart systems [350] |
| | Reinforcement | Image processing [351] |
| | | Object recognition [352] |
| | | Natural language processing [353] |
| | | Speech recognition [354] |
| | | Computer vision [355] |

## 6. Artificial intelligence for data fusion

Rapid advances and innovations in Artificial Intelligence (AI) systems, such as Machine Learning (ML) or Deep Learning (DL) methods, led to a transformation and renewal of data analysis methodologies in the past decades [346]. AI methods uncover hidden patterns in large volumes of data and often incorporate the intelligence of humans or evolutionary processes into machines or systems. ML is a group of learning techniques that automates analytical model building. DL systems can model non-linear relationships based on a neural network architecture that uses multiple layers of neurons to extract higher-level features from massive volumes of data. The term "Deep" in deep learning is defined as the concept of multiple levels or steps through which information is processed to form a data-driven model. Deep learning models primarily handle data sets with millions of rows of data. Hence, considerable time is required due to the processing of these large volumes of data points. DL is a key technology of AI systems and can be applied to build intelligent systems and automation models [347]. Fig. 15 shows the position of DL as a branch of AI. The figure defines DL as a part of ML and the broad AI area.

DL-based models have been successfully applied in a wide range of technology areas, including data fusion-based SHM [356], healthcare and medical applications [357], speech recognition [358], natural language processing [359], cybersecurity [360], smart cities [361], IoT [362], smart agriculture [363], business and financial services [240], virtual assistant and chatbot services [364], object detection and recognition [365], and recommendation systems [366].

Below, the primary reasons for the profound interest in DL-based data fusion-SHM are outlined:

– **Advances in cloud-based computation and big data**: Rapid developments in cloud-based computing and wireless technologies accommodated the deployment of online sensor networks

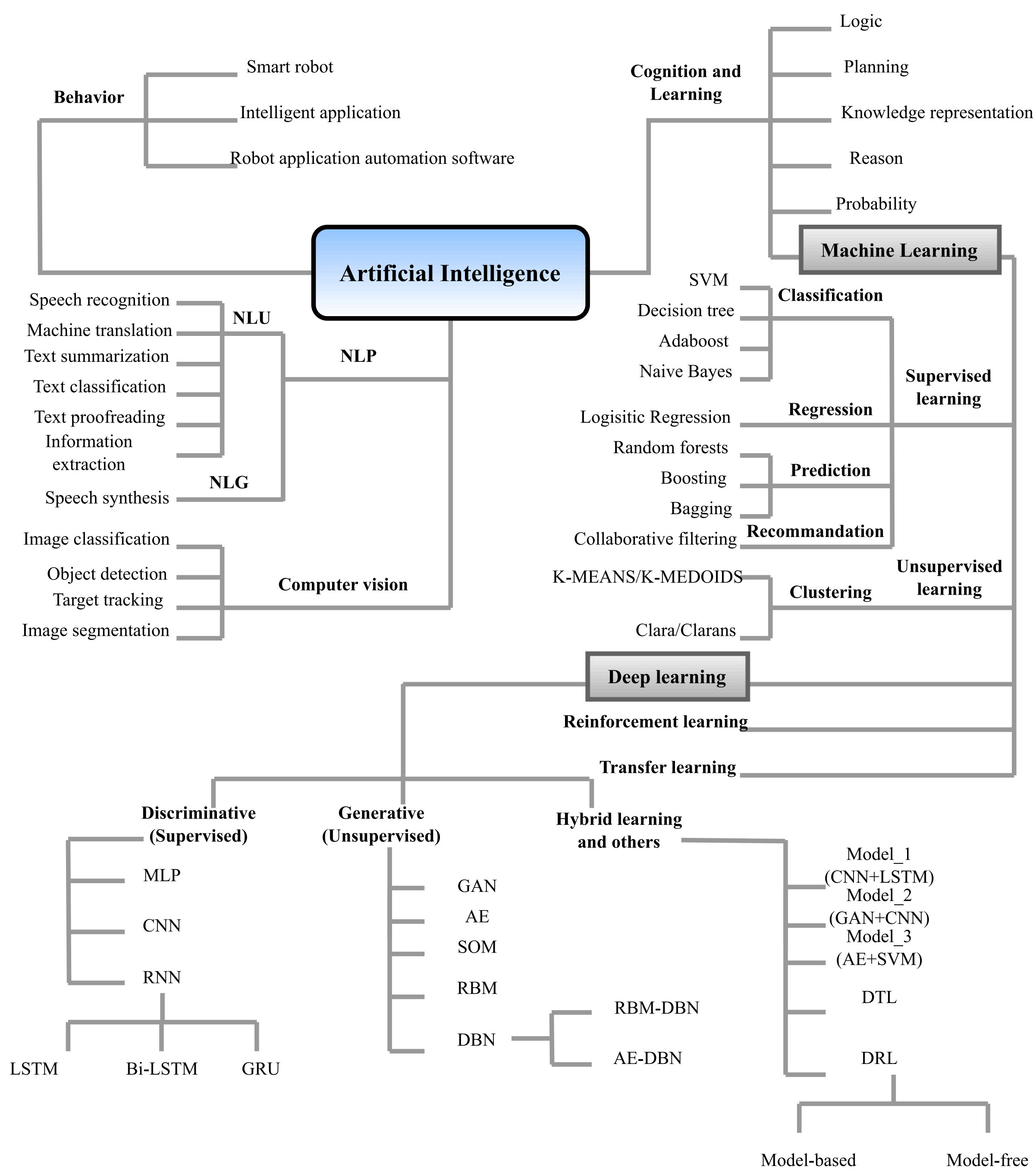


**Fig. 15.** A taxonomy of AI, ML, DL [348].

that transfer data wirelessly into cloud-based computing systems making autonomous monitoring on complex infrastructures feasible.

- **Advances in computer hardware and software**: Vast improvements in multi-core processors led to the development of powerful graphics processor units (GPUs), accelerating the processing of DL training in cloud-based online platforms.
- **Advances in data science**: The latest innovations in Data Science led to the development of DL algorithms with highly sophisticated capabilities, including feature extraction [115], outlier detection, and data recovery. These characteristics are essential for any SHM system and provide the complementary basis of DL and SHM.
- **Advances in transfer learning (TL):** In recent decades, advances in transfer learning strategies expedited the capabilities of DL technologies opening new research fields and attracting much research effort toward DL-based SHM due to their time-saving capabilities. Some examples of pre-trained networks are VGG, ResNet, and AlexNet.

Table 21 lists different DL architectures, types, and application examples. Table 22 presents different discriminative, generative, and hybrid DL models, specifies their learning types, and gives example applications.

The learning paradigms of DL models can be divided into the following categories:

- **Supervised Learning** [116]: Learning from labeled training information to predict results for unseen testing data. Classification and regression are the most popular applications of supervised learning.

**Table 22**
Deep Learning architectures.

| Model | Type | Application |
|---|---|---|
| **Discriminative architecture** | | |
| CNN | Supervised<br>Unsupervised<br>Reinforcement | Smart counting<br>Fire detection |
| RNN | Supervised<br>Unsupervised<br>Reinforcement | Text categorization<br>Pattern recognition<br>Speech recognition |
| LSTM | Supervised | Accident prediction<br>Energy management<br>Human activity recognition |
| **Generative architecture** | | |
| RBM | Unsupervised<br>Supervised | Image classification<br>Disease identification |
| DBN | Unsupervised | Activity recognition<br>Behavior prediction |
| AE | Unsupervised | Face recognition<br>Energy consumption |
| SAE | Unsupervised | Human activity recognition<br><br>Emotion recognition<br>Network intrusion |
| **Hybrid architecture** | | |
| GAN | Unsupervised | Image-to-text conversion<br>Object detection |

  - Objective: The main goal of supervised DL is to map input variables to output variables based on a set of labeled training data. Due to often highly complex non-linear relationships, big data is required to achieve this complex mapping.
  - Types: Regression and classification are two types of supervised learning approaches.
  - Advantages: Supervised DL requires a labeled data set. Therefore, the availability of accurately labeled data sets is crucial.
  - Disadvantages: The testing data set must be statistically similar to the training data set.

- **Unsupervised learning**: Unsupervised learning does not require labeled data. It clusters data by uncovering hidden patterns and relationships among data points.
  - Objective: Unsupervised DL aims to group a data set according to their similarities.
  - Types: There are two primary types of unsupervised learning, clustering techniques, such as K-means clustering, and dimensionality reduction techniques, such as Principal Component Analysis (PCA).
  - Advantages: Complex tasks can be executed where it is impossible or difficult to obtain labeled data sets.
  - Disadvantages: It often requires pre-specification of cluster numbers acquired from domain knowledge. It is adversely affected by discrepancies in the statistical properties between training and test sets.

- **Semi-supervised learning**: In semi-supervised learning, a small proportion of the available data set is labeled while the majority of the data is unlabeled.
  - Objective: Semi-supervised DL aims to bridge the limitations of supervised and unsupervised DL processes.
  - Advantages: It provides a DL solution for problems with only access to limited amounts of labeled data.
  - Disadvantages: The iterations may be unstable and the results inaccurate.

- **Reinforcement learning**: This scheme, which is positioned between supervised and unsupervised learning, provides an “agent” with the capability to learn from its surrounding environment smartly.
  - Objective: Reinforcement learning aims to improve the overall performance of DL.
  - Advantages: Complex real-world problems can be learned, stable environments with minimized trial-and-error procedures, and long-term objectives are achievable.
  - Disadvantages: Not suitable for simple tasks, large volumes of information are processed; involves heavy calculations.

In the following, DL algorithms most commonly applied for data fusion-based SHM are discussed in detail, i.e. Convolutional Neural Networks (CNNs) [367], Recurrent Neural Networks (RNNs) [368], Generative Adversarial Networks (GAN) [369] and Adversarial Autoencoder Network (AAENet) [370]. Other DL models used for SHM and data fusion include Variational Auto-Encoder Network (VAE) [371], VAE-GAN Network [372], Adversarial Variational Bayes (AVB) Network [373], Adversarially learned inference (ALI) [374] and Bidirectional GAN (BiGAN) Network [375].

- **Convolutional Neural Network (CNN)**: CNNS are feedforward networks with convolution layers and pooling layers. They are powerful in finding relationships between pixels in an image, and hence, are commonly employed for image-processing tasks. CNNS are particularly effective in capturing spatial patterns and features from visual data, making them attractive for various computer vision applications, including image classification, object detection, and image generation. They have been further successfully applied to other types of data, such as speech signals, time-series data, and sensor data, making them versatile for different domains, including data fusion applications.
  CNNs are characterized by their unique architecture, which includes convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply convolution operations to the input data, automatically allowing the network to learn local patterns and features. Pooling layers downsample the feature

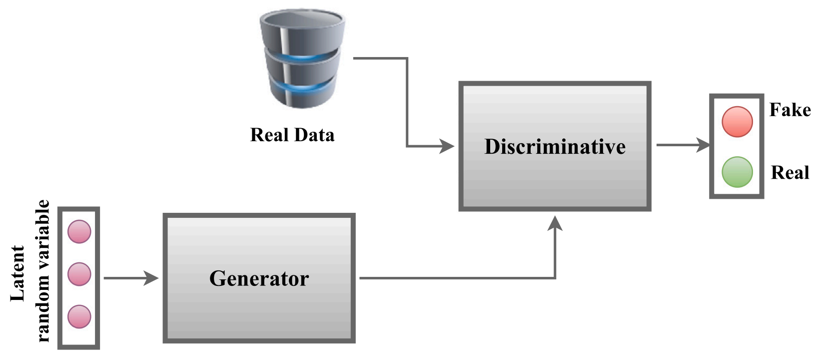


**Fig. 16.** The structure of GAN.

maps generated by the convolutional layers, reducing the spatial dimensions and allowing the network to capture a larger context. Finally, fully connected layers are used for making predictions or classifications based on the learned features.

In data fusion, CNNs can process and fuse data from multiple sources, such as images, videos, or sensor data, to learn meaningful representations and make accurate predictions or classifications. For example, in image fusion, CNNs can take inputs from multiple images captured by different sensors or modalities and learn to combine the information from these images to generate a fused image with enhanced features or improved quality. Similarly, in sensor data fusion, CNNs can take inputs from multiple sensors measuring different physical quantities and learn to extract relevant features and patterns from the fused data for tasks such as anomaly detection, prediction, or classification. Fig. 17 depicts a CNN architecture for data fusion.

CNNs have succeeded in various data fusion applications, including remote sensing, medical imaging, autonomous vehicles, and intelligent manufacturing. They can handle large amounts of data, learn complex patterns, and make accurate predictions or classifications. However, designing and training CNNs for data fusion tasks requires careful consideration of data preprocessing, model architecture, hyperparameter tuning, and model evaluation to ensure optimal performance and generalizability. In Addition, the interpretability and explainability of CNN-based fusion models may be challenging due to their deep and complex architecture, requiring further research. Various types of CNNs have been developed including R-CNN [376], SSP-Net [377], Fast R-CNN [376], YOLO [378], SSD [379], DSSD [380]. The following presents the key components of CNNs that make them effective for image-processing tasks:

- **Convolutional layers**: These layers perform convolution operations on input images, applying filters to extract local features such as edges, textures, and patterns. Convolutional layers allow CNNs to automatically learn relevant features from the input data.
- **Pooling layers**: These layers downsample the feature maps generated by convolutional layers, reducing the spatial dimensions of the data while preserving important features. Pooling helps to reduce the computational complexity of the model and capture spatial invariance.
- **Activation functions**: These functions introduce non-linearity into the model, allowing CNNs to learn complex non-linear relationships between input data and output predictions. Popular activation functions used in CNNs include ReLU (Rectified Linear Unit), sigmoid, and tanh.
- **Fully connected layers**: These layers take flattened feature maps from previous layers and connect them to the output layer, performing classification or regression tasks. Fully connected layers enable the model to predict based on the learned features.
- **Dropout and regularization**: These techniques are used to prevent overfitting, which is a common challenge in deep learning. Dropout randomly sets some of the neuron outputs to zero during training using regularization techniques, such as L1 and L2 regularization, adding penalties to the model's weights to prevent over-reliance on certain features.
- **Loss functions**: These functions quantify the difference between predicted and ground-truth labels, guiding the model to optimize its parameters during training. Common loss functions used in CNNs include categorical cross-entropy for classification tasks and mean squared error for regression tasks.
- **Optimization algorithms**: These algorithms update the model's weights during training to minimize the loss function. Popular optimization algorithms used in CNNs include stochastic gradient descent (SGD), Adam, and RMSprop.
- **Preprocessing techniques**: These techniques are often applied to the input data to normalize, augment, or preprocess it for better performance. Examples of preprocessing techniques include normalization, data augmentation, and image resizing.

These components work together in a CNN architecture to learn features from input data, make predictions, and optimize model parameters during training.

CNNs have several advantages and disadvantages, as follows:

- **Advantages:**
  * Feature learning: CNNs can automatically learn relevant features from raw data, making them well-suited for tasks such as image recognition and object detection without the need for manual feature extraction. This ability to learn hierarchical representations of data is a major advantage of CNNs.
  * Spatial hierarchies: CNNs can capture spatial hierarchies in data, learning features at multiple levels of abstraction. Convolutional layers extract local features while pooling layers downsample the data, capturing global context. This allows CNNs to learn complex patterns and representations in data.
  * Translation invariance: CNNs are inherently translation invariant, meaning they can recognize features or patterns regardless of their location in the input data. This makes them robust to changes in the position or orientation of objects, which is particularly beneficial for image-based tasks where objects can appear in different parts of an image.

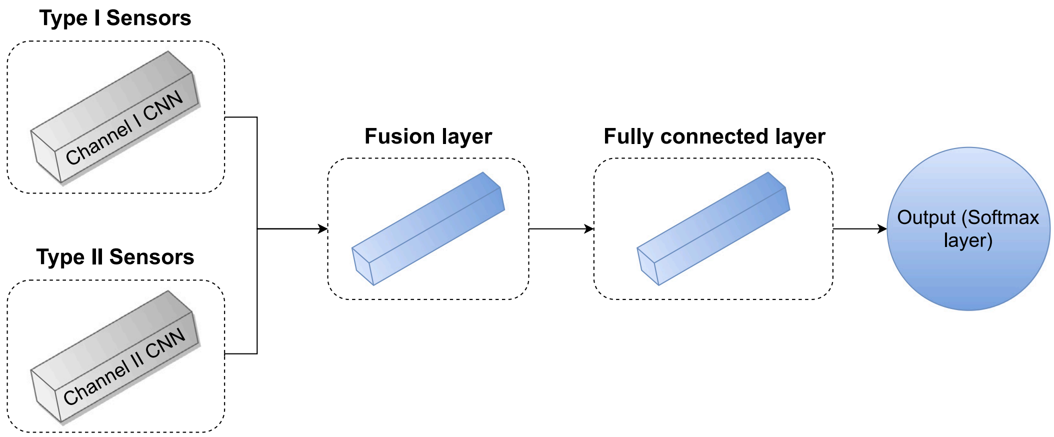


**Fig. 17.** A general CNN architecture for data fusion.

    * Scalability: CNNs can scale large datasets and complex tasks. With increasing training data, CNNs can learn more accurately and generalize representations for improved performance.

– **Disadvantages:**

    * Computational complexity: CNNs can be computationally expensive, especially with deeper architectures and large input data. Training and inference times can be high, requiring substantial computing resources.
    * Overfitting: CNNs are prone to overfitting, especially with limited training data. Overfitting occurs when the model learns to memorize the training data instead of generalizing from it, leading to poor performance on unseen data. Regularization techniques, such as dropout and weight regularization, are often used to mitigate overfitting.
    * Interpretability: CNNs are often considered black-box models, making it challenging to interpret their internal workings and understand how decisions are made. This can be a limitation in certain applications where interpretability and explainability are essential.
    * Data requirements: CNNs typically require large amounts of labeled data for training to achieve high performance. In some domains, obtaining larger amounts of labeled data can be expensive, time-consuming, or even impossible, limiting the applicability of CNNs in specific fields.
    * Data variability: CNNs can be sensitive to variations in data, such as changes in lighting, orientation, or scale. Preprocessing techniques, such as data augmentation, may be required to address these issues.

• **Recursive Neural Network (RNN)**: RNNs are a type of neural network architecture that is designed to process structured data, such as trees or graphs, by recursively applying neural operations on the input data. A feedback network that predicts new data samples based on previous output samples. The input and output data of an RNN can be a sequence of data. RNNs have been widely used in various fields, including natural language processing (NLP), computer vision, speech recognition, and time series analysis, among others. There are various types of RNNs, including LSTM, and GRU [381].

The main characteristics of RNNs are presented in the following:

– **Recursive/tree/graph structure:** RNNs are designed to process structured data, such as trees or graphs, which are represented as recursive structures. The input data is organized in a hierarchical manner, with parent nodes connected to child nodes through directed edges or other connectivity patterns.
– **Node embeddings:** Each node in the recursive structure is typically associated with an embedding or feature vector representing the information associated with that node. These embeddings can be learned during training or initialized with pre-trained embeddings, capturing the local information of each node in the structure.
– **Recursive/graph operations:** RNNs apply neural operations recursively on the nodes in the structured data. These operations can include computations such as matrix multiplications, element-wise activations, pooling, and attention mechanisms, among others. The recursive operations allow RNNs to capture contextual information and model interactions between nodes in the structure.
– **Activation functions:** RNNs use activation functions to introduce non-linearity into the computations. Common activation functions used in RNNs include sigmoid, tanh, ReLU (Rectified Linear Unit), and variants such as Leaky ReLU and ELU (Exponential Linear Unit), among others. Activation functions enable RNNs to model complex and non-linear relationships in the input data.
– **Loss functions:** RNNs use loss functions to quantify the difference between predicted outputs and ground truth labels during training. Common loss functions used in RNNs include cross-entropy, mean squared error (MSE), and variants such as weighted cross-entropy and sparse categorical cross-entropy, among others. Loss functions guide the learning process by measuring the performance of the model and driving the optimization process.
– **Optimization algorithms:** RNNs employ optimization algorithms to update the model parameters during training. Common optimization algorithms used in RNNs include stochastic gradient descent (SGD), Adam, RMSprop, and variants such as Adagrad and Nadam, among others. Optimization algorithms optimize the model parameters to minimize the loss function and improve the model's performance.
– **Backpropagation:** RNNs apply backpropagation, a widely used supervised learning technique, to compute the gradients of the model parameters with respect to the loss function. The gradients are then used to update the model parameters during training, allowing the model to learn from the input data and adjust its parameters to minimize the loss function.
– **Memory/hidden states:** RNNs have hidden states or memory cells that capture the model's internal representations and information flow through the recursive structure. Hidden states

or memory cells store information from previous steps, allowing RNNs to capture temporal dependencies and model sequential or time-dependent data.

The advantages and disadvantages of RNNs are summarized below:

– **Advantages:**

  * Sequential and temporal modeling: RNNs are well-suited for processing sequential and temporal data, as they can capture dependencies and patterns across different time steps. This makes RNNs ideal for tasks such as natural language processing, speech recognition, time series prediction, and other applications where temporal information is important.
  * Flexibility in input sizes: RNNs can handle inputs of varying sizes and structures, such as sequences of different lengths or data with varying numbers of nodes. This makes RNNs flexible and adaptable to different types of input data, including text, audio, video, and other structured or unstructured data.
  * Memory/hidden states: RNNs have hidden states or memory cells that can capture and store information from previous time steps. This allows RNNs to maintain the memory of past inputs and utilize them for making predictions or decisions in the future. This memory capability makes RNNs suitable for modeling sequences with long-term dependencies.
  * Learning complex patterns: RNNs can learn to model complex patterns and non-linear relationships in the input data, thanks to their ability to introduce non-linearity through activation functions and their recurrent connections. This makes RNNs powerful for capturing intricate patterns and representations in the data.

– **Disadvantages:**

  * Vanishing or exploding gradients: RNNs can suffer from the issue of vanishing or exploding gradients during training, which can result in difficulties in learning long-term dependencies or unstable training dynamics. This can require careful tuning of hyperparameters, such as learning rate and initialization, to mitigate these issues.
  * Computational complexity: RNNs can be computationally expensive, especially when processing long sequences or complex structures. The recursive nature of RNNs can result in a large number of parameters and computations, which can lead to increased computational costs and training times.
  * Lack of parallelism: RNNs inherently have sequential dependencies due to their recurrent connections, which can limit their ability to be parallelized during training and inference. This can result in slower training times compared to other neural network architectures that can be more efficiently parallelized.
  * Short-term memory: Although RNNs have memory or hidden states, they may struggle with capturing long-term dependencies, especially when the sequences are very long. RNNs with simple recurrent connections, such as vanilla RNNs, may suffer from the issue of forgetting earlier inputs as new inputs are processed, which can result in limitations in modeling long-term dependencies.
  * Overfitting: RNNs, like other neural networks, can be susceptible to overfitting, where the model may memorize the training data and not generalize well to unseen data. Regularization techniques, such as dropout, L1/L2 regularization, and early stopping, may be required to mitigate overfitting in RNNs.

• **Generative Adversarial Network (GAN)**: Goodfellow Ian et al. [382] proposed GAN in 2014, and it has since become one of the most popular unsupervised DL models. A GAN comprises a system of two networks, i.e., the Generative network (GNet) and the Discriminator network (DNet), that compete with each other. The GNet is trained to generate results that are close to the real results. The DNet, on the other hand, is a simple binary classifier with a single output scalar that distinguishes samples generated by the GNet from actual data using the multilayer perception algorithm. GANs have been successfully used in many DL-based data fusion-SHM applications. The simplified structure of GAN is shown in Fig. 16. The advantages and disadvantages of GANs are summarized in the following:

  – **Advantages:**

    * Generate realistic data: GANs are capable of generating realistic and high-quality data samples, such as images, audio, text, and more. GANs learn to generate data that is similar to the training data, making them suitable for tasks such as image synthesis, data augmentation, and content creation.
    * Unsupervised learning: GANs can learn from unlabeled data, making them capable of unsupervised learning. This eliminates the need for labeled data during training, which can be expensive or time-consuming to obtain in many applications. GANs can generate synthetic data samples without the need for labeled data for training, making them versatile for various tasks.
    * Diversity in generated data: GANs can generate diverse and novel data samples by learning the underlying distribution of the training data. This allows for the generation of new and unique data samples that may not exist in the original training dataset, making GANs suitable for creative tasks and data augmentation.
    * Robust to noise: GANs are robust to noise and perturbations in the input data, as they learn to generate data from a probabilistic distribution. This makes them resilient to noise or small variations in the input data, allowing them to generate plausible and realistic data samples even with imperfect input data.

  – **Disadvantages:**

    * General: Network training is difficult and it requires different types of data. The learning process needs close supervision to ensure that the training is performed accurately.
    * Training instability: GANs can be challenging to train and may suffer from training instability. The adversarial training process involves a generator and discriminator network competing against each other. This can lead to issues such as mode collapse (where the generator produces limited diversity) or vanishing gradients (where the discriminator becomes too confident). Careful tuning of hyperparameters and network architectures, as well as proper monitoring and stabilization techniques, are necessary to mitigate these issues.
    * Mode collapse: GANs can suffer from mode collapse, where the generator produces only a limited subset of the target data distribution, resulting in a lack of diversity in the generated samples. This can result in the generated data being unrealistic and not fully capturing the variability of the training data.

* Evaluation challenges: Evaluating the performance of GANs can be challenging, as there is no objective criterion for measuring the quality of generated data. Traditional evaluation metrics may not be suitable for GANs, and subjective human evaluation may be required, which can be time-consuming.
* Data quality dependency: The performance of GANs is highly dependent on the quality and quantity of the training data. GANs may struggle with generating high-quality data if the training data is limited or of low quality. Additionally, GANs may also inherit biases present in the training data, leading to generating biased data.
* Computational complexity: GANs can be computationally expensive, especially when generating high-resolution images or processing large datasets. Training GANs may require substantial computational resources, including powerful GPUs and large amounts of memory, which can be a limitation for some applications.
* Lack of interpretability: GANs are typically black-box models, making it challenging to interpret and understand the internal workings of the generator and discriminator networks. This lack of interpretability can be a limitation in applications where the explainability or interpretability of the generated data is important.

Most metrics for evaluating fusion results of GAN can be introduced into its loss function [383]. The loss function of a GAN provides the required supervised information for training. In contrast, the loss function of the generator is a statistical expectation. Since the expectation does not represent the properties of an individual observation, it is not sufficient for image fusion where a unique image fusion from multisource images is sought. Other than statistical expectation, other loss functions, including content loss, spectral loss, and perception loss, can be introduced into the primary generator of the data fusion loss function. As such, structural similarity (MS-SSIM) is another loss function often included in GANs for image fusion [384]. Below, a common combination of different loss functions in the GAN generator for image fusion is presented [383]:

$$\begin{aligned} l_G = &\underbrace{l_{\mathrm{G}}^{\mathrm{ADV}}}_{\text{Adversarial loss}} + \lambda_1 \underbrace{l_{\mathrm{G}}^{\mathrm{PXL}}}_{\text{Pixel content loss}} \\ &+ \lambda_2 \underbrace{l_{\mathrm{G}}^{\mathrm{FTR}}}_{\text{Feature perception loss}} + \lambda_3 \underbrace{l_{\mathrm{G}}^{\mathrm{SAM}}}_{\text{Spectral loss}} + \ldots \end{aligned} \tag{17}$$

– **Adversarial Autoencoder Network (AAENet)**: As proposed by Makhzani et al. [370], AAENet is a probabilistic autoencoder that matches the aggregated posterior of its hidden code vector to a prior distribution of any type to perform variational inference. AAENets are trained to achieve two objectives: (1) to satisfy a reconstruction error criterion and (2) to match a structured prior distribution to the obtained posterior distribution of the aggregated (latent) representation. Encoders learn to convert data distributions into prior distributions, and decoders learn to map the prior distribution onto data distributions after training. Over the years, different types of AAENets have been developed; these include the following:

  * **Sparse Autoencoder (SAE):** Sparsity loss is applied on a hidden layer to prevent the output layer from copying the input data.
  * **Deep Autoencoder:** A stack of Restricted Boltzmann Machines (RBMs) is employed for pretraining to unroll the data structure. A deep autoencoder can be fine-tuned using back-propagation.
  * **Contractive Autoencoder:** Contractive penalty is applied in the activation unit of latent space stated by data. Unsupervised learning is supported by encoding unlabeled data.
  * **Convolutional Autoencoder:** Weights are shared among all convolution layers to preserve spatial locality.
  * **Variational Autoencoder:** A typical generative adversarial model where new data is generated to augment the sample data.
  * **Denoising Autoencoder:** This algorithm aims to regenerate accurate data from corrupted (noisy) input data.

Below, the advantages and disadvantages of AAENets are summarized:

* **Advantages:**
  · Unsupervised learning: AAENets allow for unsupervised learning, which means they can learn from unlabeled data without the need for labeled data during training. This makes them suitable for tasks where labeled data is scarce or unavailable, and they can potentially leverage large amounts of unlabeled data for training.
  · Data generation: AAENets are capable of generating new data samples by sampling from the learned latent space and passing them through the decoder. This makes them suitable for generating synthetic data for data augmentation, content creation, and other creative tasks. Generated data can be used for various applications, such as data synthesis, data augmentation, and data generation for rare events.
  · Latent space representation: AAENets learn a lower-dimensional latent space representation of the input data, which can capture meaningful representations and features of the data. This can be useful for tasks such as data compression, data visualization, and data exploration. The latent space can also serve as a compact representation of the data, which can be useful for downstream tasks such as classification or clustering.
  · Robustness to noise: AAENets are robust to noise and perturbations in the input data as they learn to generate data from a probabilistic distribution. This can help in generating plausible and realistic data samples even with imperfect input data and can be advantageous in scenarios where the data may be noisy or incomplete.
* **Disadvantages:**
  · Training instability: The adversarial training process in AAENets can be challenging to stabilize, similar to other GAN-based architectures. Careful tuning of hyperparameters, network architectures, and monitoring techniques may be required to mitigate issues such as mode collapse, vanishing gradients, and training instability. Training AAENets can require careful experimentation and optimization.
  · Computational complexity: AAENets, like other GAN-based architectures, can be computationally expensive to train and generate data, especially when dealing with large datasets or high-dimensional data. The training process may require significant computational resources, such as GPUs or distributed computing, which may limit its usability in some applications with resource constraints.

· Interpretability: The latent space representation learned by AAENets may not always be easily interpretable, as it is typically a lower-dimensional representation of the input data. This may limit its usability in applications where interpretability of the latent space is important, such as in domains where explainability and interpretability are crucial, such as healthcare or finance.
· Evaluation challenges: Evaluating the performance of AAENets can be challenging, as there is no objective criterion for measuring the quality of generated data. Traditional evaluation metrics may not be suitable, and subjective human evaluation or domain-specific evaluation may be required. Evaluating the performance and reliability of AAENets can be challenging and may require careful consideration of evaluation methodologies.

Bhagat et al. [385] developed a spatially constrained adversarial autoencoder to fuse the infrared image's spectral content and visible image. The residual adversarial network–a primary building block of the encoder and decoder units in an adversarial network–was employed as a regularization term in a residual autoencoder architecture to generate a more realistic fused image.

– **Digital Twins**: Digital twins have emerged as one of the most powerful tools for data fusion in SHM, combining data from multiple sources and analyzing it to safeguard the safety of structures and the health of their occupants. A digital twin serves as a dynamic, virtual representation of physical structures, enabling the fusion of various data streams for enhanced decision-making and maintenance strategies. Digital twins are used in data fusion for SHM in the following ways:

  * **Sensor Data Integration:** Digital twins amalgamate data from a diverse array of sensors such as accelerometers, strain gauges, temperature sensors, and vibration sensors installed on a structure. This comprehensive data fusion offers a holistic view of the structure's behavior and health, enabling accurate condition assessment.
  * **Multimodal Data Fusion:** Digital twins facilitate the fusion of various data types, including sensor data, images, and even textual documentation about the structure. This holistic approach enhances the understanding of structural behavior, helping detect anomalies and patterns that might be missed by analyzing individual data sources.
  * **Environmental Data Fusion:** Integrating environmental data such as weather conditions, temperature, humidity, and seismic activity with the digital twin enables a more accurate assessment of a structure's response to external factors. This fusion enhances the prediction of potential structural vulnerabilities and helps in optimizing maintenance strategies.
  * **Geospatial Data Fusion:** Geographic information systems (GIS) data, such as location-specific terrain features and geological information, can be fused with the digital twin. This integration allows for a better understanding of how the surrounding environment affects the structure's health and stability.
  * **Historical Data Incorporation:** By fusing historical data with real-time sensor readings, digital twins provide insights into the structure's long-term behavior, helping engineers identify trends and anomalies that might indicate deterioration or damage.
  * **Machine Learning Integration:** Digital twins can incorporate machine learning models that continuously learn from data and provide predictive insights. The fusion of these predictive models with real-time sensor data enables early anomaly detection and proactive maintenance planning.
  * **Remote Sensing Data Fusion:** Satellite imagery, LiDAR scans, and drone-based data can be fused with the digital twin to create a comprehensive 3D model of the structure. This fusion enhances the accuracy of defect detection and aids in monitoring hard-to-reach areas.
  * **Human-Generated Data Fusion:** The fusion of reports, maintenance records, and expert opinions with the digital twin provides a more comprehensive understanding of the structure's history, vulnerabilities, and maintenance requirements.
  * **Real-Time Decision Support:** Through data fusion, digital twins offer real-time insights and decision support to operators and maintenance teams. By analyzing integrated data, digital twins provide actionable recommendations for maintenance, repair, and operational adjustments.
  * **Predictive Maintenance Strategies:** The integration of data from various sources enables the development of strategies that leverage the insights of the digital twin for predictive maintenance. The benefits of this approach include enhanced maintenance schedules, reduced downtime, and a longer lifespan for structures.

  Dan et al. [386] developed a full-bridge traffic load monitoring system based on information fusion of weigh-in-motion (WIM) and multi-source heterogeneous machine vision. The system was set up to measure traffic loads and lightweight sensors were used to provide structural response information. Wan et al. [387] investigated the feature recognition, diagnosis, and forecasting performance of Semi-Supervised Support Vector Machines (S3VMs) for brain image fusion Digital Twins (DTs). Liu et al. [388] systematically described and identified the importance of data fusion in aircraft predictive maintenance using a digital twin framework.

In Table 23, we review recent papers based on DL-based data fusion methods in SHM systems.

### 6.1. Machine learning for data fusion

The capabilities of machine learning (ML) techniques provide exceptional synergies for data fusion, which involves the integration and analysis of data from multiple sources to obtain more accurate and reliable information. The following outlines the key aspects of ML in data fusion:

– **Feature selection and extraction:** ML algorithms can automatically select relevant features from the data and extract meaningful representations, which are then used for data fusion. This helps reduce the data's dimensionality, improving efficiency and enhancing the quality of the fused data.
– **Fusion methods:** ML techniques can be employed for fusion methods that combine data from multiple sources, such as sensor data, image data, or text data. ML algorithms, such as Bayesian networks, decision trees, and ensemble methods, can be applied to combine data from different sources, handle uncertainties, and make decisions based on the fused data.
– **Data alignment and calibration:** ML can be used to align and calibrate data from different sources, which may have variations in terms of scale, units, or formats. Techniques such as regression, normalization, and data preprocessing methods, can be applied to align and calibrate data from different sources to ensure consistency and accuracy in the fused data.
– **Data imputation and completion:** ML models can be used to impute missing or incomplete data in the fused data set. Techniques such as k-nearest neighbors, regression, and deep learning-based methods can be employed to fill in missing data points and complete the fused data, which helps obtain a more complete and accurate representation of the underlying phenomenon.

**Table 23**
Review of recent papers on the DL-based data fusion method.

| Methods | Num. | Exp. | Description | Ref. |
|---|---|---|---|---|
| GANs | ✓ | ✓ | This paper presents a novelty-classification framework based on GANs using high-dimensional feature space extracted from low-sampled data classes. The framework is mainly developed to generate new data objects for SHM systems and sensor output validation (SOV) problems. | Soleimani-Babakamali et al. [389] |
| GANs | ✓ | ✓ | This paper proposes a novel two-stage method using GANs for bridge health monitoring where recorded raw signals (acceleration data) are fused by a GAN network. | Rastin et al. [390] |
| AE | ✓ | | This paper proposes a motor fault identification algorithm using an AAENet-based deep neural network. Accordingly, the AAENet was developed for data fusion for fault identification in Cyber–Physical–Social Systems (CPSSs). | Wang et al. [391] |
| AE | ✓ | | This work proposes a novel AAENet-based unsupervised clustering method based on density peak-spectral clustering (Dpeak-SC) for unsupervised feature extraction of space-target ISAR images. | Yang et al. [392] |
| VAE | ✓ | ✓ | This paper proposes a novel VAE-based method to process responses of a structure and reduce high-dimensional data to a low-dimensional feature space, and then restore the original data from the low-dimensional representations. | Ma et al. [393] |
| CNN | ✓ | ✓ | This paper presents a novel framework for convolutional fusion called the collaborative fusion convolutional neural network (CFCNN). A multilevel shrinkage denoising module (MSDM) is developed for extracting multilevel, modality-specific features. A central fusion module (CFM) is introduced to explore further and integrate cross-modal features, drawing inspiration from the intermediate fusion scheme. | Xu et al. [367] |
| RNN | ✓ | ✓ | Using a hybrid RNN, a novel damage detection method is presented in this paper. For deep feature extraction, a CNN is also used. Comparing this proposed method with one that only contains deep features, the discrimination ability is improved by fusing both spatial and temporal features. | Bui-Tien et al. [394] |

- **Fusion model training and optimization:** ML techniques can be used to train and optimize fusion models based on historical or labeled data. Techniques such as supervised learning, unsupervised learning, and reinforcement learning can be employed to train and optimize fusion models to achieve higher accuracy and performance in data fusion tasks.
- **Anomaly detection:** ML can be applied to detect anomalies or outliers in the fused data, which helps in identifying unexpected patterns, behaviors, or events. Anomaly detection techniques, such as clustering, classification, and outlier detection algorithms, can be used to detect anomalies in the fused data, which is useful in various applications, including fraud detection, fault diagnosis, and anomaly monitoring.
- **Decision making and prediction:** ML algorithms can be used to make decisions and predictions based on the fused data. Techniques such as classification, regression, and time-series analysis can be applied to make decisions, predictions, or recommendations based on the fused data, which helps in guiding actions, optimizing processes, and improving outcomes in various domains.

The advantages and disadvantages of ML in data fusion are summarized below.

- **Advantages:**
  * Improved accuracy: ML techniques can help improve data fusion accuracy by leveraging algorithms' power to automatically learn patterns, relationships, and correlations in the data from multiple sources.
  * Efficient data integration: ML algorithms can effectively integrate data from multiple sources, handle uncertainties, and make decisions based on the fused data, which helps obtain a more comprehensive and accurate representation of the underlying phenomenon.
  * Enhanced decision-making: Utilizing ML in data fusion enables better decision-making by providing insights and predictions based on the combined data from multiple sources, which helps in informed decision-making, optimizing processes, and improving outcomes.
  * Automation and scalability: ML allows for automation and scalability in data fusion tasks, as the algorithms can process and analyze large volumes of data from multiple sources efficiently and effectively.
- **Disadvantages:**
  * Data quality and variability: The quality and variability of data from multiple sources can impact the accuracy and reliability of the fused data. Data preprocessing, calibration, and alignment may be required to address these challenges.
  * Model complexity: ML models used in data fusion can be complex, requiring significant computational resources, training data, and model optimization efforts.
  * Lack of interpretability: ML used in data fusion can lack interpretability, making it difficult to understand and explain the reasoning behind the fused data and decision-making processes. This can be a challenge in domains where interpretability and explainability are fundamental, such as healthcare, finance, or legal applications.
  * Data privacy and security: Data fusion may involve integrating data from multiple sources, which can raise concerns about data privacy and security. Ensuring the fused data's confidentiality, integrity, availability, and compliance with data protection regulations can be challenging in ML-based data fusion.
  * Data heterogeneity and scalability: Data from multiple sources may exhibit heterogeneity in terms of formats, scales, and units, which can pose challenges in data fusion.

Scalability can also be a concern when dealing with large volumes of data from diverse sources, as it may require significant computational resources and processing time to perform data fusion tasks efficiently.

* Data uncertainty and noise: Data from multiple sources may contain uncertainties, errors, and noise, which can affect the accuracy and reliability of the fused data. ML models used in data fusion need to account for these uncertainties and noise to ensure robust and reliable results.
* Model overfitting: ML algorithms used in data fusion may be prone to overfitting, especially when dealing with small or imbalanced datasets. Overfitting can lead to overly optimistic performance during training but may result in poor generalization and performance on unseen data.

### 6.2. Deep learning for data fusion

Deep learning (DL), a subset of machine learning, has been widely utilized in data fusion to leverage its capabilities in handling large-scale, complex, and high-dimensional data. DL models, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs), among others, have been applied in data fusion tasks to improve the accuracy, efficiency, and interpretability of fused data. The following presents the advantages and disadvantages of using DL in data fusion:

- **Advantages:**
  * Feature learning: DL models can automatically learn features from raw data, eliminating the need for manual feature extraction. This can be particularly useful in data fusion tasks where data from multiple sources may have different representations or formats.
  * High accuracy: DL techniques can achieve high accuracy in data fusion tasks, as they can capture complex patterns and relationships in large and diverse datasets. This can improve decision-making and prediction accuracy in various domains, such as image and speech recognition, natural language processing, and sensor data fusion.
  * Scalability: DL models are highly scalable and can handle large-scale datasets with millions of data points. This makes them suitable for data fusion tasks involving massive amounts of data, such as in fields like remote sensing, finance, and social media analysis.
  * Non-linearity: DL algorithms can capture non-linear relationships in data, which may not be captured by traditional linear models. This allows them to model complex data interactions and dependencies, making them suitable for data fusion tasks involving multi-modal and multi-dimensional data.
- **Disadvantages:**
  * Data requirements: DL models usually require a large amount of labeled data for training, which may not always be available in data fusion tasks, especially in domains with limited data or where data collection is costly or time-consuming.
  * Model complexity: DL models are typically complex, with many parameters, layers, and hyperparameters. This can make them computationally expensive to train and optimize and may require specialized hardware and software resources.
  * Lack of interpretability: DL models can be challenging to interpret and explain, as they operate as black boxes, making it challenging to understand the reasoning behind the fused data and decision-making processes. This can be a limitation in domains where interpretability and explainability are critical, such as healthcare and legal applications.
  * Overfitting: DL models are susceptible to overfitting, especially when dealing with minor or imbalanced datasets. Overfitting can lead to poor generalization performance and reduced model reliability on unseen data.

The following subsections review the state-of-the-art in artificial intelligence for data fusion by categorizing the current works into three categories: signal-level data fusion, feature-level data fusion, and decision-level data fusion. Various types of artificial intelligence are reviewed in each category.

### 6.3. Signal-level data fusion

The lowest level of data fusion in the Luo Kay architecture is signal-level fusion. A sensor's raw data inputs are used to generate data outputs with high accuracy, reliability, and a low level of noise. In other words, features are extracted from observations to reflect an aspect of those observations directly. Many signal fusion applications involve pixel, image, and other signal-level models. Signal-level data fusion combined with artificial intelligence offers numerous benefits: improved signal quality, enhanced signal interpretation, increased sensor redundancy, and expanded application possibilities. However, it also comes with challenges related to data synchronization, calibration and normalization, data complexity and dimensionality, and data quality and reliability, which need to be carefully addressed to ensure the effective fusion of signals for accurate and reliable data analysis. The following presents information on the use of unsupervised and supervised AI for signal-level data fusion.

#### 6.3.1. Signal-level data fusion based on supervised learning

In supervised learning, a model is trained using labeled data, i.e., the desired output or target variable is known. The model learns from the labeled data to predict or decide on new, unseen data. The algorithm is provided with a set of input features and their corresponding output labels. The goal is to learn a mapping function that can accurately predict the output labels for new input features.

Signal-level data fusion based on supervised learning is a technique used to combine data from multiple sources or sensors into a single representation using supervised algorithms. Data fusion aims to improve the fused data's accuracy, reliability, and comprehensiveness compared to individual data sources.

The process of signal-level data fusion based on supervised learning typically involves the following steps:

- Data collection: Data is collected from multiple sources or sensors. These sources can be heterogeneous in nature, such as different types of sensors, data modalities, or data formats.
- Data preprocessing: The collected data is preprocessed to remove noise, handle missing values, and normalize the data to ensure consistency across different sources.
- Feature extraction: Features are extracted from the preprocessed data to represent the relevant information that can be used for the supervised learning process. This can involve techniques such as dimensionality reduction, feature selection, or feature engineering.
- Labeling: If labeled data is available, it assigns labels or target values to the extracted features. Labeling can be done manually or using automated techniques, depending on the availability of labeled data.
- Training: The labeled data is then used to train a supervised learning model, such as a classification or regression algorithm. The model learns to map the extracted features to the corresponding labels or target values.

– Fusion: Once the supervised learning model is trained, it can be used to predict the labels or target values for the unseen data from different sources. The predictions from other sources are combined using fusion techniques, such as averaging, weighted averaging, or decision-level fusion, to obtain a single fused output.
– Evaluation: The fused output is evaluated based on predefined performance metrics to assess the fused data's accuracy, reliability, and comprehensiveness. If the performance is unsatisfactory, the fusion process can be iteratively refined by adjusting the model parameters, feature extraction techniques, or fusion techniques.

Below, the advantages and disadvantages of signal-level data fusion based on supervised learning are outlined.

– **Advantages:**
    * Improved accuracy: By combining data from multiple sources, the fused data can often have higher accuracy than individual data sources. The supervised learning model can leverage complementary information from different sources to make more accurate predictions or decisions.
    * Enhanced reliability: Data fusion can also improve the reliability of the fused data by reducing the impact of noise or errors in individual data sources. The fused data can be more robust and less prone to outliers or inconsistencies, leading to more reliable results.
    * Comprehensive information: Data fusion can provide a more comprehensive representation of the underlying phenomenon by integrating information from different sources. This can lead to a more holistic and complete understanding of the data, which can be valuable in decision-making or problem-solving scenarios.

– **Disadvantages:**
    * Data heterogeneity: Data from different sources or sensors can be heterogeneous in nature, with variations in data modalities, formats, or scales. This can pose preprocessing, feature extraction, and fusion challenges, as the data needs to be aligned or transformed to ensure compatibility across different sources.
    * Labeling and ground truth: Obtaining labeled data for training supervised learning models can be challenging, especially when dealing with multiple data sources. Labeling data from different sources may require domain expertise and can be time-consuming, costly, or subjective. In some cases, obtaining ground truth or reference data for evaluating the fused data can also be problematic.
    * Model complexity: Combining data from multiple sources can increase the complexity of the supervised learning model, as it needs to handle multiple inputs, feature extraction techniques, and fusion techniques. This can require more computational resources and longer training times and may challenge model interpretability or explainability.

Supervised learning for signal-level data fusion can be employed for numerous applications. The following provides an overview of various application fields and discusses recent research examples.

– **Applications:**
    * Remote sensing: Data fusion from satellite imagery, airborne sensors, and ground-based sensors can improve land cover classification, change detection, and environmental monitoring.
    * Sensor networks: Data fusion from sensor networks can enhance situational awareness, event detection, and anomaly detection in smart cities and the Internet of Things (IoT) areas.
    * Finance and economics: Data fusion from multiple financial and economic data sources, such as stock prices, economic indicators, social media sentiment, and news articles, can provide more accurate predictions for stock market trends, economic forecasts, and investment decision-making.
    * Healthcare: Data fusion from electronic health records, wearable devices, genetic data, and medical imaging can improve disease diagnosis, personalized treatment plans, and patient monitoring in healthcare settings.
    * Transportation: Data fusion from various sensors in transportation systems, such as GPS, traffic cameras, and vehicle sensors, can enhance traffic management, route optimization, and accident detection for intelligent transportation systems.
    * Weather and climate: Data fusion from weather stations, satellite imagery, and numerical weather prediction models can improve weather forecasting, climate modeling, and disaster management, such as flood prediction and early warning systems.
    * Agriculture: Data fusion from satellite imagery, weather data, soil data, and crop yield data can enhance crop monitoring, precision farming, and yield prediction, leading to better decision-making for farmers and optimizing agricultural practices.
    * Environmental monitoring: Data fusion from different sources, such as satellite imagery, ground-based sensors, and citizen science data, can improve environmental monitoring and conservation efforts, including biodiversity mapping, forest monitoring, and pollution detection.
    * Military and defense: Data fusion from multiple sensors, such as radars, cameras, and drones, can enhance situational awareness, target detection, and surveillance in military and defense applications.

Banerjee and Das [57] combined a multisensor data fusion with short-term Fourier transforms (STFTs) and time duration-based observer models to form a hybrid fault detection method. Their system investigated three types of states: healthy, degraded, and failed. Sensor data were first preprocessed in STFT, which is primarily based on frequency level and amplitude. Following training with labeled data, an SVM classifier transformed the input signals into a high-dimensional feature space and separated signals linearly into original signals and fault signals. Then, a threshold-based sensing system received signals from classifiers and judges stating the system was working. In a system, the threshold is a level of tolerance. When a signal crosses a safety valve, it results in an unwanted response, leading to a state change. The system output was finally divided into three categories: healthy system (i.e., the state of the system does not change during observation), degraded system (i.e., the changes are within a tolerance level), and failed system (some signals do indeed cross the safety valve). In the proposed model, a motor's working state was monitored at intervals of time with a prior alarm if any undesirable conditions occurred. Considering that the sensors captured data nonlinearly, the authors concluded that SVM is an excellent nonlinear pattern recognition tool that simultaneously ensures accuracy and performance in fault diagnosis. Classification accuracy and average classification performance were improved compared to the system without fusion.

By optimizing a Bayesian approach to data fusion with SVM, Challa et al. [395] compressed information using a Bayesian approach. A support vector was created by minimizing the objective function of SVM and transforming input signals into an approximation function of input signals. Due to the lack of useful information in these signals, other non-support vectors were discarded. To achieve sound efficiency based on different practical applications, a kernel dictionary was provided for the SVM to be modified as needed. Tests were conducted in a density estimator system, and the model showed excellent data compression performance. The fusion efficiency and extensibility of the method were both found to be good. Since the model required a large number of training samples to verify its strength, it made it less robust and stable.

A data fusion algorithm based on SVMs was proposed by Fahmy et al. [396]. A high level of accuracy was achieved by combining fingerprints and iris data using SVM. Despite this, traditional linear SVMs did not perform well enough. An important aspect of the study was the study of a technique called score normalization. It was demonstrated in this work that some previous publications did not consider this procedure necessary in statistical learning fusion like SVM. As an important internal component of the SVM procedure, score normalization helped in transforming raw data into a uniform pattern. Traditional SVM models are more efficient and robust when normalized. SVM can reduce time consumption in both the training and testing phases since it can deal directly with the result. It was demonstrated that the improved SVM model exhibits high fusion quality and stability with the CASIA and FVC2004 databases by introducing and testing a number of score normalization methods based on Radial Basis SVM.

In many application environments, such as human–machine interfaces and motion analysis, precise location is crucial. Here, a multi-sensor system is used to capture positional information about a target from multiple viewpoints. To obtain complete knowledge of the target's location, fusion models must overcome the imperfections in these data sets. Kolanowski et al. [397] developed a navigation system using Elman Artificial Neural Networks (ANNs), which are good at solving nonlinear problems, particularly in prediction. Data sets from sensors were first analyzed by the Automatic Heading Reference System (AHRS). An Elman ANN model with 9 input and 3 output neurons was trained with input and output data sets. Input and output layers were separated by at least one hidden layer. Also, the previously hidden layer was stored in a context-sensitive layer that was only connected to the hidden layer. It can be viewed as a representation of feedback when it comes to context-sensitive layers. The number of neurons in the feedback loop was changed for better performance. Compared to AHRS, Elman ANN produced few errors, indicating that it is a viable alternative for detecting position. It is possible to reduce the time costs of trigonometric operations and matrix operations by reducing the number of operations involved. As a result, this system achieved efficiency and quality.

A semi-supervised learning method based on the fusion of multi-sensor information was proposed by Zhong et al. [398] for diagnosing hydraulic directional valve faults. This method generated pseudo labels for large amounts of unmarked data using a small amount of data with fault labels. Using a multi-sensor fusion algorithm, a high-confidence pseudo label could be obtained, and an adaptive threshold model like the generative countermeasure network was utilized to intelligently select pseudo labels without human intervention, similar to generative countermeasure networks. It was shown that the multi-sensor information fusion algorithm can generate high-confidence pseudo tags and that the adaptive threshold model is capable of screening effective pseudo-tag samples by generating appropriate thresholds to accelerate classification convergence. For different types of hydraulic valves in different engineering fields, the average diagnosis accuracy of this method after five iterations could reach 99.72% and 99.00%.

#### 6.3.2. Signal-level data fusion based on unsupervised learning

Signal-level data fusion based on unsupervised learning refers to a process where multiple datasets, typically coming from different sources or modalities, are combined or fused into a single representation using unsupervised learning techniques. In unsupervised learning, the model learns from unlabeled data without explicit supervision or labeled examples.

The process of signal-level data fusion based on unsupervised learning typically involves the following steps:

– Data preparation: The individual datasets from different sources or modalities are collected and preprocessed to ensure that they are compatible for fusion. This may involve data cleaning, normalization, feature extraction, and other data preprocessing techniques.
– Unsupervised learning: Unsupervised learning techniques are then applied to the preprocessed datasets to learn meaningful representations or patterns in the data. Common unsupervised learning algorithms used for data fusion include clustering algorithms such as k-means, hierarchical clustering, and Gaussian mixture models, dimensionality reduction techniques such as principal component analysis (PCA), autoencoders, and t-SNE, and other unsupervised methods such as self-organizing maps (SOM) and generative models like variational autoencoders (VAEs) or generative adversarial networks (GANs).
– Fusion of representations: Once the unsupervised learning algorithms have learned representations or patterns from the individual datasets, the representations are combined or fused into a single representation. This can be done through various techniques such as feature concatenation, feature averaging, or more advanced methods like late fusion, early fusion, or decision-level fusion, depending on the specific application and the type of data being fused.
– Evaluation and analysis: The fused representation is then evaluated and analyzed to assess its quality, usefulness, and effectiveness for the desired application. This may involve quantitative measures such as clustering accuracy, classification accuracy, or other domain-specific evaluation metrics, as well as qualitative analysis to interpret the fused representation and gain insights from the data.

In the following, the advantages, disadvantages, and application examples of signal-level data fusion based on unsupervised learning are presented.

– **Advantages:**
    * Utilization of unlabeled data: Unsupervised learning techniques do not require labeled data, which can be expensive or time-consuming to obtain. Unlabeled data can often be easily collected from various sources, making it more accessible for data fusion. Unsupervised learning allows for the utilization of vast amounts of unlabeled data, potentially leading to more comprehensive and representative fused representations.
    * Capturing complex patterns: Unsupervised learning algorithms can capture complex and nonlinear patterns in the data, which may not be apparent through manual feature engineering or traditional fusion techniques. By learning representations from data without relying on predefined labels, unsupervised methods can reveal hidden patterns, structures, or relationships that may not be easily discovered using other approaches.
    * Flexibility and scalability: Unsupervised data fusion techniques are often flexible and scalable, allowing diverse data sources or modalities to be fused. These algorithms can be applied to various types of data, such as text, images, audio, and sensor data, making them applicable to a wide range of applications. Unsupervised data fusion can also handle large datasets enabling the processing of big data sets.
    * Enhanced data analysis: Signal-level data fusion based on unsupervised learning can provide enhanced data analysis capabilities by integrating information from multiple sources into a unified representation. This can lead to improved data understanding, identification of hidden patterns, and enhanced decision-making, resulting in better insights and outcomes of various tasks.

– **Disadvantages:**

  * Lack of ground truth for evaluation: Unsupervised data fusion techniques often lack ground truth or labeled data for evaluation. The absence of labeled data makes it challenging to evaluate the fused representation's quality objectively. Evaluation criteria may be subjective or domain-specific, and it can be difficult to compare and benchmark different methods. Careful consideration of evaluation strategies and appropriate performance metrics is required.
  * Choice of algorithms and hyperparameters: Selecting suitable unsupervised learning algorithms, hyperparameters, and fusion strategies can significantly impact the quality of the fused representation. Various algorithms are available, each with its own strengths and limitations. Choosing suitable algorithms and hyperparameters for a specific application or dataset can be challenging and may require experimentation and tuning.
  * Interpretability and explainability: Unsupervised learning algorithms may produce difficult-to-interpret or explain representations. The lack of interpretability and explainability can hinder understanding the fused representation and the insights gained from the data. Interpretable and explainable unsupervised learning techniques are still an active area of research, and careful consideration may be required for applications where interpretability is important.
  * Data heterogeneity and noise: Data heterogeneity and noise can pose challenges in unsupervised data fusion. Data from different sources or modalities may have varying levels of quality, noise, or inconsistencies, which can affect the quality of the fused representation. Preprocessing and handling data heterogeneity and noise can be complex, and careful data preprocessing and feature extraction may be required to ensure the quality of the fused representation.
  * Overfitting and generalization: Unsupervised learning algorithms can be prone to overfitting, especially when dealing with complex and high-dimensional data. Ensuring the generalization and robustness of the fused representation to unseen data can be challenging. Techniques such as regularization, cross-validation, or ensemble methods may be needed to mitigate overfitting and improve generalization performance.

– **Applications:**

  * Image and video analysis: Unsupervised data fusion techniques can be used to fuse information from multiple image or video sources, such as different cameras, sensors, or modalities, to improve object recognition, scene understanding, or video summarization.
  * Natural language processing (NLP): Information from multiple text sources can be combined by applying unsupervised data fusion. Text sources, such as news articles, social media posts, or customer reviews, can be processed to enhance sentiment analysis, topic modeling, or text summarization.
  * Sensor networks: Unsupervised data fusion can be used in sensor networks to combine data from multiple sensors, such as temperature, humidity, pressure, or motion sensors, to improve anomaly detection, event detection, or environmental monitoring.
  * Health informatics: In health informatics, unsupervised data fusion techniques can be applied to combine data from various sources, such as electronic health records, wearable devices, or genomic data, to improve disease prediction, personalized medicine, or patient monitoring.
  * Recommender systems: Unsupervised data fusion can be used in recommender systems to combine user behavior data, content data, or contextual data to provide more accurate and personalized recommendations for products, movies, or services.
  * Fraud detection: Unsupervised data fusion can be applied in fraud detection to combine data from multiple sources, such as transaction data, user behavior data, or network data, to improve the identification of fraudulent activities or anomalies.
  * Remote sensing: In remote sensing applications, unsupervised data fusion techniques can be used to combine data from multiple sensors, such as satellite imagery, radar data, or LiDAR data, to improve land cover classification, change detection, or disaster monitoring.
  * Industrial automation: Unsupervised data fusion can be applied in industrial automation to combine data from multiple sources, such as sensors, machines, or production data, to optimize production processes, predictive maintenance, or quality control.

Radar systems with high resolution have special demands in terms of data processing efficiency since they handle large amounts of raw data and require real-time fusion for monitoring and tracking targets. A fast data fusion algorithm based on clustering was proposed by Li and Wang [399]. Using this algorithm, raw data was divided into clusters based on one-dimensional distances. The authors calculated that the proposed algorithm has a calculation complexity of O(m*n). Data fusion experiments in the same application environment showed that the model performed better than K-means, Hierarchy, and other algorithms. A significant amount of noise was considered by the authors when collecting data from the radar system. As part of the algorithm, the noise was removed at the end to increase its robustness.

In a similar manner, Wang et al. [400] developed a solution for multi-target tracking based on hierarchical clustering algorithms. Their paper describes target tracking problems when multiple radars detect the same target. The study investigated irregular target routes, i.e., radar tracks are either not uniform in time, or do not have a common interval. Hierarchical clustering was used to solve various problems. The data preprocessing was followed by the definition and calculation of Hausdorff distance that defines the similarity between two tracking data sets. The researchers employed cluster search trees to represent the data sets that have Hausdorff distances as a class. A hierarchical clustering tree was created by merging similar classes into a new class. The final clustering process was the most important step in fusion, and an improved K-means algorithm was designed for this task. Using real radar data, the algorithm was shown to be effective, stable, and accurate in tracking.

The design of routing protocols becomes one of the most important aspects of wireless sensor networks (WSNs) in order to achieve good fusion efficiency. Routing protocols must consider many factors, including the topology of the entire network, fusion node capabilities, and time limits for valid signals captured by sensors. A routing protocol proposed by Xiao and Liu [401] used un-even clustering and simulated annealing. The two obvious differences between LEACH (Low Energy Adaptive Clustering Hierarchy) and the new protocol were the uneven initial clustering and the dynamic time interval for cluster head selection. Based on position information and energy information, the simulated annealing algorithm clustered the nodes at the start of the protocol. The next step was to transmit the sensor data sets to the cluster head for their corresponding sensor. During data fusion, cluster heads send the fused information to its next hop. Real-time cluster heads were permitted to continue if a residual energy threshold was reached. In the absence of a cluster head, the base station would choose a new cluster head immediately and begin a new round. As a result of the proposed protocol, the network's lifetime was prolonged, and the total amount of energy consumption was reduced. By leveraging a distributed data fusion function, a WSN with a distributed data fusion function could maximize efficiency from a resource usage perspective. In this way, the efficiency of fusion was greatly improved. Rather than testing the sensor in a real environment, experiments were conducted using a sensor simulation tool.

Data fusion with fuzzy logic is based on a weighted algorithm. Due to their excellent performance, fuzzy logic-based fusion algorithms have attracted a lot of attention, particularly contributing to calculating weighted factors and dealing with imprecise data. Raw data in a WSN, however, does not work well with the traditional weighted fuzzy logic algorithm because invalid data is frequently collected in a real-world environment leading to serious deviations from the aggregate. According to Wang et al. [402], this problem can be solved by improved fusion methods involving k-mean clustering. Prior to calculating weighted factors, the raw data were first preprocessed using K-means clustering. A series of clusters were created by dividing raw data into sections and arranging error data with high variance into specific groups. Data in these clusters containing errors or useless data could be reduced in weight to improve fusion quality. Comparisons of simulated datasets and traditional weighted fuzzy logic algorithms were undertaken for fusion accuracy. Based on their theory, the method achieves better fusion quality and efficiency and is also robust to noise. However, a real-world evaluation of this method is still needed.

Using clustering for data fusion, Alyannezhadi et al. [403] proposed a method for combining uncertainty systems based on data fusion. Unknown systems are systems with several unidentified characteristics or mathematical models. As a result, data processing is difficult since the explicit patterns of the system are unknown. The data fusion algorithm proposed by the researchers included clustering, prediction, and updating parts. In their work, multilayer perceptrons (MLPs) were trained using data to optimize their prediction ability in the clustering phase. The results of the fusion were updated throughout the whole system. This model was designed to solve the main problem of inconsistency and uncertainty in unknown systems. Results from experiments with real temperature data from five Internet companies demonstrated that the algorithm is robust and eliminates data inconsistencies. The algorithm can also be applied to other multisensor data fusion scenarios, indicating its extensibility.

### 6.4. Feature-level data fusion

Feature-level data fusion, also known as attribute-level data fusion, involves combining features or attributes extracted from raw sensor data from multiple sources to create a fused representation that captures relevant information for a specific task or application. AI techniques can be used to process and fuse these features, providing valuable insights and enabling various applications. Feature-level data fusion with AI offers benefits in terms of enhanced feature representation, improved model performance, efficient data processing, and flexibility. However, it also comes with challenges related to feature selection and extraction, data heterogeneity, data availability and completeness, and model interpretability, which need to be carefully addressed to ensure an effective fusion of features for accurate and reliable data analysis.

#### 6.4.1. Feature level data fusion based on supervised learning

Feature-level data fusion based on supervised learning involves combining features or attributes extracted from raw sensor data using supervised algorithms. In this approach, labeled data is used to train the model, which then makes predictions or classifications on new, unseen data. The fused features are used as input to the model to learn patterns and relationships between the features and the target variable, allowing for improved performance in various applications. The general process for feature-level data fusion based on supervised learning is outlined below.

– Data collection: Gather data from multiple sources or modalities containing the features of interest. This can include data from sensors, images, text, or any other relevant data source.
– Feature extraction: Extract relevant features from the data sources. This may involve preprocessing, feature engineering, or dimensionality reduction techniques to obtain meaningful and representative features from each source.
– Labeling: Annotated or labeled data is required for supervised learning. This involves associating the extracted features with corresponding labels or ground truth information. The labels can be obtained through manual annotation or existing labels in the data.
– Training: Train a supervised learning model using the labeled data, such as a classification or regression model. The model learns the relationship between the features and the labels based on the training data.
– Fusion: Combine the features from the different sources using a fusion technique or algorithm. This can involve concatenating, averaging, or weighing the features from different sources to create a fused feature representation.
– Prediction or inference: Use the trained model and the fused feature representation to make predictions or inferences on new, unseen data. This can involve classification, regression, or any other relevant task, depending on the nature of the data and the problem at hand.
– Evaluation: Evaluate the performance of the fused features and the supervised learning model using appropriate evaluation metrics. Depending on the specific application, this may involve measures such as accuracy, precision, recall, F1-score, or any other relevant performance metrics.
– Fine-tuning: Based on the evaluation results, fine-tune the fusion technique, algorithm, or supervised learning model as needed to optimize the performance.
– Deployment: Once the model is optimized, deploy it in the intended application or system for real-world use, and monitor its performance for continuous improvement.

The benefits, challenges, and application examples of feature-level data fusion based on supervised learning are presented in the following.

– **Advantages:**
    * Improved prediction or classification accuracy: Supervised learning algorithms can leverage the fused features to create models that are trained on labeled data, leading to improved accuracy in predicting or classifying the target variable. The combined features can capture relevant information from multiple sources, resulting in more accurate and reliable predictions or classifications.
    * Ability to handle non-linear relationships: Supervised learning algorithms can capture non-linear relationships between features and the target variable, allowing for more complex and sophisticated modeling. The fused features can provide a more comprehensive representation of the underlying information, enabling the model to capture intricate patterns and relationships that may not be apparent when using individual features.
    * Robustness to noisy or incomplete data: Supervised learning algorithms can handle noisy or incomplete data by leveraging the fused features. The combined features can provide a more robust representation that is less affected by individual sensor noise or missing data, leading to more reliable and accurate predictions or classifications.
    * Interpretability of model predictions: Some supervised learning algorithms, such as decision trees or linear regression, can provide interpretable model predictions. This can be

useful in applications where interpretability and explainability are essential, such as healthcare or finance, allowing for a better understanding of the underlying factors driving the predictions.

– **Disadvantages:**

 * Labeling and availability of labeled data: Supervised learning requires labeled data for training the model, which may not always be readily available or costly. Labeling data from multiple sources and ensuring consistency in labeling can pose challenges in the data fusion process.
 * Feature selection and extraction: Choosing relevant features from raw sensor data and extracting meaningful information can be challenging. Feature selection, feature extraction, or feature engineering techniques may be required to identify the most informative features and create a compact and discriminative fused representation.
 * Overfitting and model complexity: Supervised learning models can be prone to overfitting, especially when the number of features is large or when the data is limited. Managing model complexity, avoiding overfitting, and ensuring generalization performance can be challenging, requiring careful model selection and hyperparameter tuning.
 * Data heterogeneity: Sensor data from different sources may exhibit heterogeneity in terms of data types, scales, or units, which can affect the fusion process. Handling data heterogeneity and ensuring consistency in the fused representation may require careful data preprocessing, normalization, or transformation techniques.

– **Applications:**

 * Image and video processing: In computer vision applications, features extracted from images or videos, such as color, texture, shape, and motion features, can be fused using supervised learning to improve object recognition, scene understanding, and action recognition tasks.
 * Sensor networks: In wireless sensor networks, data from multiple sensors can be fused at the feature level using supervised learning to improve tasks such as target tracking, environmental monitoring, and anomaly detection. For example, combining temperature, humidity, and pressure readings from different sensors can help in accurately predicting weather patterns.
 * Medical diagnosis: In healthcare applications, features from multiple medical sensors or modalities, such as patient vitals, lab results, and medical images, can be fused using supervised learning to aid in disease diagnosis, prognosis, and treatment planning. For instance, combining features from different medical tests can improve the accuracy of cancer detection.
 * Speech and audio processing: In speech and audio processing applications, features extracted from audio signals, such as spectral, pitch, and temporal features, can be fused using supervised learning to improve tasks such as speech recognition, speaker identification, and audio event detection.
 * Finance and economics: In finance and economics, feature-level data fusion using supervised learning can be used to combine information from multiple sources, such as stock prices, economic indicators, and news sentiment, to improve financial prediction, portfolio optimization, and risk assessment tasks.
 * Internet of Things (IoT): In IoT applications, where data is collected from various sensors and devices, feature-level data fusion using supervised learning can be used to combine features from different sources to enable smart decision-making, anomaly detection, and predictive maintenance.
 * Transportation and traffic management: In transportation and traffic management, features from different sensors, such as traffic cameras, GPS, and weather sensors, can be fused at the feature level using supervised learning to improve traffic flow prediction, congestion detection, and transportation planning.
 * Environmental monitoring: In environmental monitoring applications, features from different sensors, such as air quality sensors, water quality sensors, and weather sensors, can be fused using supervised learning to improve tasks such as pollution prediction, disaster management, and ecosystem monitoring.
 * Smart city applications: In smart city applications, feature-level data fusion using supervised learning can be used to combine data from various sources, such as traffic sensors, weather sensors, social media, and citizen feedback, to enable smart urban planning, resource management, and decision-making.
 * Industrial automation: In industrial automation, features from different sensors, such as temperature sensors, pressure sensors, and vibration sensors, can be fused at the feature level using supervised learning to improve tasks such as predictive maintenance, process optimization, and quality control in manufacturing processes.

Pouteau and Stoll [404] proposed a selective fusion algorithm based on SVMs for land cover classification. As a result of SVM's ability to process data from both mono- and multi-sources, the authors hypnotized that SVM would outperform previous fusion models in this field. The accuracy may deteriorate when non-relevant sources are utilized in simplex multi-source fusion models. A selective SVM, however, may be able to handle it with on-the-fly classifications and multi-source fusions. The proposed algorithm was shown to be effective and stable through experiments on real data sets. As shown in this paper, it is not limited to the classification of tropical rainforests. The algorithm applies to other remote sensing problems involving multi-sensory and Geographic Information System (GIS) data, indicating its extensibility.

A multisensory data fusion algorithm based on ANN, SVM, and NBC was developed by Starzacher and Rinner [405]. Each data processing node in an embedded real-time environment does not have ample resources. There are, however, strict requirements on the processing time of an applied fusion algorithm since the embedded multi-sensor fusion system proposed in [405] included a center node, multiple sensor nodes, and a sensor node that assists a single node in making decisions. Three fusion methods were tested using four real-world datasets in an embedded test platform. The performance of models was measured by the time it took for the classification to complete and the classification rate. According to the results of the experiments, SVM outperformed the classical methods and had the shortest classification time. It was concluded that the three fusion methods perform reasonably well in an embedded system.

SVMs are increasingly used to solve learn-to-rank problems, transforming them into formalized binary classifications. Cao et al. [406] used a ranking SVM as part of a meta-search engine based on fusion. The paper presented a cross-media meta-search engine that supports both text-based and content-based retrieval. Users will request results from several member search engines, which will then be merged together into a meta-search engine. Among the key features of this engine is its ”result fusion”, which combines results from all members and generates a ranking list. In this field, it is common for literature to give engines a common weight while ignoring the specific conditions and performances of each one. In their paper, Cao et al. used supervised learning to solve this problem. By changing a function form, the ranking SVM model converts the ranking problem into a binary classification problem. The algorithm builds training sets based on the users' orders for each document from the result sets. Following that, linear merged functions and constraint relationships are used to train the weights of the features. The authors evaluated the fusion model's precision using many parameters as part of their simulations. An extensive amount of data from the WikipediaMM2008 database was used for the experiments. All assessment measurements showed that ranking SVMs perform better than other methods regarding accuracy and performance. There is no mention of the model's efficiency in this paper, which requires further study.

An online tool wear estimation environment was developed using artificial neural networks [407]. To prevent product quality degradation caused by serious tool wear, monitoring tool wear is essential in manufacturing processes. Data fusion is used to estimate online tool wear since there is a great demand for this service. An information fusion model based on neural networks was presented here, including feature extraction, feature preprocessing, and feature fusion. In order to train the neural networks offline, training datasets and testing datasets were obtained from optical microscopes. This enabled the estimation of tool wear by the system once the tool's features were available online. For assessing and acquiring the best estimation result, different feature groups were extracted and tested. Using training data sets generated from laboratories and industrial environments with different noise levels, the system was demonstrated to be practicable and effective.

*6.4.2. Feature level data fusion based on unsupervised learning*

Feature-level data fusion based on unsupervised learning involves combining features from multiple sources or modalities without using labeled data for training. The below describes the general process for feature-level data fusion based on unsupervised learning:

- Data collection: Gather data from multiple sources or modalities that contain the features of interest, without any labeled information.
- Feature extraction: Extract relevant features from the data sources using techniques such as preprocessing, feature engineering, or dimensionality reduction, to obtain meaningful and representative features from each source.
- Unsupervised learning: Apply unsupervised learning algorithms, such as clustering, dimensionality reduction, or autoencoders, to learn patterns, structures, or relationships within the extracted features from different sources.
- Fusion: Combine the features from the different sources using a fusion technique or algorithm, based on the unsupervised learning results. This can involve techniques such as clustering-based fusion, principal component analysis (PCA)–based fusion, or variational autoencoder-based fusion, among others.
- Fused feature representation: Obtain a fused feature representation that captures the combined information from the different sources, which can be used for downstream tasks.
- Downstream tasks: Use the fused feature representation for various downstream tasks, such as classification, clustering, or anomaly detection, depending on the specific application.
- Evaluation: Evaluate the performance of the fused feature representation and the unsupervised learning-based fusion technique using appropriate evaluation metrics, such as clustering accuracy, silhouette score, or reconstruction error, depending on the specific application.
- Fine-tuning: Based on the evaluation results, fine-tune the fusion technique, algorithm, or hyperparameters as needed to optimize the performance.
- Deployment: Once the fusion technique is optimized, deploy it in the intended application or system for real-world use, and monitor its performance for continuous improvement.

The following presents the advantages, disadvantages, and application examples of feature-level data fusion based on unsupervised learning.

- **Advantages:**
  * Enhanced information integration: Feature-level data fusion allows for the integration of information from multiple sources, which can result in a more comprehensive and accurate representation of the data, leading to improved performance in downstream tasks.
  * Flexibility and adaptability: Unsupervised learning-based feature-level data fusion can adapt to different types of data sources or modalities, making it versatile for various applications without relying on predefined labels.
  * Reduced reliance on labeled data: Feature-level data fusion based on unsupervised learning does not require labeled data for training, which can be advantageous when labeled data is scarce or costly to obtain, and allows for leveraging unlabeled data for better performance.
- **Disadvantages:**
  * Lack of labeled data for supervision: Unsupervised learning methods do not rely on labeled data, which can result in lower accuracy or reliability compared to supervised methods that have access to labeled data for training.
  * Selection of appropriate algorithms and techniques: Choosing the right unsupervised learning algorithms, fusion techniques, or hyperparameters can be challenging and may require careful experimentation and optimization to achieve optimal results.
  * Interpretability and explainability: The fused feature representation obtained from unsupervised feature-level data fusion may lack interpretability and explainability, as the relationship between the features and the labels is not explicitly learned, which can pose challenges in understanding the underlying patterns or structures.
- **Applications:**
  * Image and video processing: Feature-level data fusion can be used to combine visual features from multiple sources, such as images or videos, for tasks such as image recognition, object detection, or video summarization. For example, fusing features extracted from multiple modalities, such as RGB images, depth maps, and infrared images, can lead to improved object recognition in computer vision applications.
  * Audio and speech processing: Feature-level data fusion can be applied to combine audio features from multiple sources, such as speech signals, audio recordings, or acoustic sensors, for tasks such as speech recognition, speaker identification, or emotion recognition. For instance, combining features from multiple microphones or sensors can enhance the accuracy of speech recognition in noisy environments.
  * Sensor networks: Feature-level data fusion can be used to combine data from multiple sensors in sensor networks for tasks such as environmental monitoring, target tracking, or anomaly detection. For example, fusing data from different types of sensors, such as temperature, humidity, and pressure sensors, can provide a more comprehensive and accurate view of the environment being monitored.
  * Healthcare: Feature-level data fusion can be employed in healthcare applications to combine data from multiple sources, such as electronic health records, wearable devices, or medical imaging, for tasks such as disease diagnosis, personalized treatment recommendation, or health monitoring. For instance, fusing features from multiple modalities, such as clinical data and genomics data, can lead to more accurate predictions of disease outcomes.

  * Internet of Things (IoT): Feature-level data fusion can be used in IoT applications to combine data from multiple devices or sensors, such as smart home devices, wearable devices, or smart city sensors, for tasks such as activity recognition, anomaly detection, or predictive maintenance. For example, fusing data from different types of sensors, such as motion sensors, temperature sensors, and light sensors, can provide a more holistic view of the environment being monitored.

A hierarchical fusion system was proposed by Xiao et al. [408] using four fusion layers to process alerts. Prior to primary alert reduction, the data sets undergo alert pretreatment. Different alerts that arrive during a certain period of time were compared based on factors, such as protocol type, source IP, target IP, etc. Whenever all attributes in two alerts were the same, thereby eliminating false alerts, these two alerts were combined first. The purpose of alert verification was to achieve high fusion quality by comparing the alert itself with its target machine. A periodic scan of the protected network environment was performed using this module to attain high efficiency. The burden of services could also be reduced by eliminating many false alarms. To classify alerts, fuzzy clustering methods were employed, which mainly group alerts based on the type of attack. Clusters of alerts with the same target IP address were grouped together. This was followed by generating the fuzzy similarity matrix for each group. Fuzzy clustering was used with an appropriate threshold to divide the alerts at the end. An attack scenario was constructed by correlating alerts in the same class based on attack knowledge. The results of two test data sets showed high performance in reducing redundant alerts showcasing the capabilities of the proposed system.

### 6.5. Decision level data fusion

Decision-level data fusion is a technique where decisions or outputs from multiple sources are combined to make a final decision or inference. AI algorithms can be used in decision-level data fusion to learn how to optimally combine decisions from different sources.

#### 6.5.1. Decision level data fusion based on supervised learning

Decision-level data fusion based on supervised learning involves using supervised algorithms to combine decisions or outputs from multiple sources following the steps below.

- Data collection: Data from multiple sources or sensors is collected, which could be in the form of raw data, feature vectors, or decisions.
- Decision generation: Each source or sensor processes the data and generates its own decision or output using a supervised learning algorithm. Supervised learning algorithms require labeled training data, where the inputs (features) and corresponding outputs (labels) are known.
- Training of supervised learning algorithm: The supervised learning algorithm is trained using the labeled training data from each source or sensor. The algorithm learns to map the inputs (data from different sources) to the outputs (decisions) based on the provided labels.
- Decision combination: Once the supervised learning algorithm is trained, it can be used to combine the decisions from multiple sources. The decisions may be weighted or aggregated based on the learned parameters or predefined rules.
- Decision output: The combined decision or inference is generated as the final output, which can be used for further downstream tasks, such as decision-making, action planning, or control.

The benefits, challenges, and application examples of decision-level data fusion based on supervised learning are outlined in the following.

- **Advantages:**
  * Improved decision accuracy: Supervised learning algorithms can learn to combine decisions from multiple sources based on labeled training data, leading to improved decision accuracy.
  * Flexibility and adaptability: Supervised learning algorithms can adapt to different types of data sources, decision types, or fusion rules, making them versatile for various applications.
  * Robustness and reliability: Decision-level data fusion based on supervised learning can increase the robustness and reliability of decision-making by incorporating redundant information from multiple sources, which can improve decision-making in uncertain or noisy environments.
  * Scalability: Supervised learning algorithms can handle large amounts of labeled training data, making them suitable for applications where data from multiple sources are available.
- **Disadvantages:**
  * Data quality and consistency: The quality and consistency of data from different sources can vary, which can impact the accuracy and reliability of decision-level data fusion. Data preprocessing, calibration, or normalization may be required to address these challenges.
  * Availability of labeled training data: Supervised learning algorithms require labeled training data, which may not always be available or may be expensive to obtain, especially in scenarios where multiple sources or decisions are involved.
  * Interpretability and explainability: Supervised learning algorithms can sometimes be complex and difficult to interpret or explain. InterpretableML techniques or explainable AI methods may be needed to address this challenge.
- **Applications:**
  * Multi-sensor data fusion: In fields such as remote sensing, robotics, autonomous vehicles, and smart environments, decision-level data fusion can be used to combine data from multiple sensors, such as cameras, Lidar, radar, or other types of sensors, to make decisions or inferences about the environment, objects, or events.
  * Biomedical applications: In healthcare and biomedical research, decision-level data fusion can be used to integrate data from different sources, such as medical records, imaging data, wearable devices, or genetic data, to aid in disease diagnosis, treatment planning, or monitoring of patient conditions.
  * Financial applications: In finance and investment, decision-level data fusion can be used to combine information from multiple sources, such as market data, economic indicators, news feeds, or social media data, to make investment decisions, risk assessments, or portfolio optimizations.
  * Security and surveillance: In security and surveillance applications, decision-level data fusion can be used to combine data from different sources, such as video feeds, audio data, sensor data, or social media data, to detect anomalies, identify threats, or monitor activities in real-time.
  * Natural language processing: In natural language processing applications, decision-level data fusion can be used to combine information from multiple sources, such as text documents, audio data, or sentiment analysis results, to perform tasks such as text classification, sentiment analysis, or information retrieval.

  * IoT: In IoT applications, decision-level data fusion can be used to integrate data from multiple sensors or devices, such as smart home devices, wearables, or industrial sensors, to make decisions or trigger actions based on the combined information.
  * Human activity recognition: In fields such as sports, fitness, or human–computer interaction, decision-level data fusion can be used to combine data from different sensors, such as accelerometers, gyroscopes, or biometric sensors, to recognize human activities, gestures, or behaviors.

A typical decision fusion model was proposed by Bigdeli et al. [409] based on multiple SVMs and Na¨ıve Bayes. A combination of light detection and ranging (LIDAR) and hyperspectral data was discussed in the context of remote sensing data from multiple sensors. As a first step, LIDAR and hyperspectral data were analyzed to extract useful features for identifying objectives in the next stages. In the following phase, the features captured in the previous phase were classified using a one-against-one multiclass SVM method based on radial basis functions (RBF). Each feature space was classified using SVMs. An optional classical fusion method, the Nave Bayes model, combines data sets from single classifiers. Model performance was evaluated using overall accuracy and kappa coefficient. Compared to the original LIDAR, hyperspectral data, or any simple integrated model of these two data types, the proposed model showed better results. In an experiment conducted at the University of Houston using data sets captured by an official mapping organization around the campus, this method was shown to maximize the advantages of LIDAR and hyperspectral by extracting features, classifying features, and combining them. The paper further evaluated and compared fusion performance highlighting the advantages of the proposed model.

An anomaly-based intrusion detection system was provided by Giorgio et al. in [410] as a preliminary version of [411]. Several classifiers were present in their work. Based on the characteristics of the feature, traffic connections, and data packets were divided into three groups-intrinsic features, traffic features, and content features. Each feature set was analyzed with a corresponding classifier. The classifier can distinguish attack patterns based on feature sets describing normal and abnormal network patterns through training with a large group of data sets. To evaluate the effectiveness of the system, the authors employed a three-layer neural network as a classifier along with five different fusion rules. It was found that the Multiple Classifier System is more efficient than an individual classifier that deals with all extracted features in terms of detection rate, false alarm rate, and generalization abilities. As well as providing the best overall performance regarding false alarms, errors, and average costs, A-Posteriori DCS fusion provided the best overall results.

Decision fusion strategies also employ clustering in the final step [49]. As such, a nuclear power crack detection algorithm based on deep learning was proposed by Chen et al. [412]. The inspection of nuclear power cracks is an essential component of nuclear applications in case of an incident. The detection of tiny cracks and noisy patterns using vision-based algorithms was proposed by some researchers, but open issues remain. Using Nave Bayes and clustering, Chen et al. overcome critical problems. To make the final decision, their clustering model grouped tubelets for a whole crack with Euclidean distance after the former modules' crack detection results were aggregated in tubelets. Nave Bayes discarded false positive tubelets, and the clustering model grouped the tubelets together for a whole crack based on their Euclidean distance. Real crack datasets were used to test this algorithm. Based on experimental results, the effectiveness of this method was shown to have improved over the past methods showcasing stability and robustness owing to its capability to detect robust patterns in noisy environments.

#### 6.5.2. Decision level data fusion based on unsupervised learning

Decision-level data fusion based on unsupervised learning involves combining decisions or outputs from multiple sources without relying on labeled data for training. Instead, unsupervised learning algorithms are used to discover patterns, relationships, or structures in the data, and then decisions are made based on the learned representations. The process of decision-level data fusion based on unsupervised learning typically involves the following steps:

– Data aggregation: Raw data from multiple sources are collected and aggregated into a single dataset.
– Feature extraction: Unsupervised learning algorithms, such as clustering or dimensionality reduction techniques, are applied to the aggregated data to extract relevant features or representations.
– Decision making: Decisions are made based on the extracted features or representations, using techniques such as voting, averaging, or rule-based methods.
– Evaluation: The performance of the decision-level data fusion is evaluated based on predefined metrics or criteria.

Decision-level data fusion based on unsupervised learning offers several benefits and challenges as summarized below.

– **Advantages:**
  * No labeled data required: Decision-level data fusion based on unsupervised learning does not rely on labeled data for training, which can be a limitation in scenarios where labeled data is scarce or expensive to obtain.
  * Flexibility: Unsupervised learning algorithms can adapt to different data sources and do not require predefined labels or classes, making them flexible for handling diverse data types or modalities.
  * Robustness: Unsupervised learning can handle noisy or incomplete data and can discover hidden patterns or structures that may not be apparent in individual data sources.
  * Scalability: Unsupervised learning techniques can handle large-scale datasets, making them suitable for applications with big data.
– **Disadvantages:**
  * Lack of ground truth: Since unsupervised learning does not rely on labeled data, evaluating the performance of decision-level data fusion based on unsupervised learning can be challenging, as there may be no ground truth for comparison.
  * Interpretability: Unsupervised learning algorithms may produce complex or abstract representations, making it difficult to interpret or explain the decisions made based on these representations.
  * Sensitivity to algorithm selection: The choice of unsupervised learning algorithms can significantly impact the performance of decision-level data fusion, and finding the optimal algorithm for a given application may require experimentation and tuning.
  * Computational complexity: Some unsupervised learning algorithms can be computationally intensive, especially for large-scale datasets, which may pose challenges in real-time or resource-constrained environments.

• **Applications:**
  – Anomaly detection: Decision-level data fusion based on unsupervised learning can be used to detect anomalies or outliers in data by combining decisions from multiple sources.

  - Clustering or grouping: Unsupervised learning can be used to group or cluster data from different sources based on similarity or affinity, such as customer segmentation, image or video clustering, or document grouping.
  - Outlier detection: Unsupervised learning can be used to identify outliers or abnormal events in data by comparing decisions from multiple sources.
  - Data fusion in sensor networks: Decision-level data fusion based on unsupervised learning can be used in sensor networks to combine data from multiple sensors for tasks such as localization, tracking, or event detection.

In Table 24, we review recent papers on AI-based data fusion methods in SHM systems.

### 6.6. Fusion using language models

Large Language Models (LLMs) gained significant traction in recent years due to their impressive performance, pre-training capabilities, and efficiency in terms of time and cost. This section outlines a potential avenue of future research on the application of LLMs in the context of SHM for data fusion of various input types, including sensor measurement and imagery.

Among the many approaches to enhancing the capabilities of machine models to interpret human language, language modeling (LM) stands out as one of the most significant. Accordingly, an LM is designed to capture the probability of generating sequences of words within a context, thereby predicting the likelihood of forthcoming or absent tokens. The field of language modeling has advanced substantially over the past decade progressing through four distinct phases:

- **Statistical Language Models (SLMs):** SLMs played an important role in the early stages. By using statistical methods, these models aimed at understanding language patterns, and facilitating predictions based on word frequency and co-occurrence. This approach provided a basis for foundational language understanding.
- **Neural Language Models (NLMs):** The emergence of neural networks significantly changed language modeling. Complex linguistic relationships can be captured using neural network architectures in NLMs. It marked a significant improvement in the efficiency and accuracy of language understanding.
- **Pre-trained Language Models (PLMs):** PLMs represented the next evolution in language modeling. Initially, these models were trained using vast amounts of text data and then fine-tuned for specific tasks. In this approach, transfer learning was utilized to accelerate the adaptation and proficiency of models in various language contexts.
- **Large Language Models (LLMs):** LLMs are at the forefront of language modeling. The models, which are usually based on the Transformer architecture, include a large number of parameters, sometimes reaching the thousands of millions. To acquire a deep understanding of language patterns and nuances, they are trained on massive text datasets. A few examples of LLMs are the Generative Pre-trained Transformer 3 (GPT-3), the Pathways Language Model (PaLM), the Galactica, and the Large Language Model Meta AI(LLaMA).

LLMs have found compelling applications for data fusion, providing a new dimension of combining and analyzing disparate data sets. Traditionally, data fusion has been associated with sensor data, but LLMs introduce the concept of text-based data fusion, in which textual information from a variety of sources is amalgamated to provide enhanced insights and decision-making capabilities. LLMs can gather and evaluate huge amounts of textual data, extract contextual relationships, detect events, gauge sentiment, and even facilitate cross-modal fusion with multimedia content. By synthesizing knowledge, providing real-time insights, and enabling human–machine collaboration, LLMs enhance the data fusion process, enabling organizations to make better decisions by leveraging language intelligence along with traditional sensor data.

An example of fusing input data for LLMs can be found in a recent paper by Hu et al. [450]. To improve automatic speech recognition (ASR), Hu et al. proposed training a single multilingual language model for shallow fusion in a variety of languages. Using a mixture of experts in LLM, i.e., a generalist language model (GLaM), the researchers expanded the scope of the multilingual LM to encompass up to 84 languages. GLaM was subsequently applied to a multilingual shallow fusion task based on an end-to-end model designed to improve performance. Bianco et al. [451] introduced a novel approach to enhancing image captions by fusing captions generated by State-of-the-Art (SOTA) LLM models. Instead of training the existing models, it ranked captions from existing models using an image–text metric and fused the top two using an LLM, resulting in more consistent and human-like captions. This method showcased the potential for improved image captioning by leveraging the strengths of different SoTA models and aligning automated systems with human-generated descriptions for better quality and training possibilities. Jiang et al. [452] have recently published a paper that demonstrates the fusion of input data for LLMs. The authors proposed a framework based on the LLM-Blender framework that employed PairRanker and GenFuser modules to leverage multiple LLMs' strengths for improved performance. In this work, PairRanker distinguished candidate outputs using a cross-attention approach, while GenFuser fused top-ranked candidates to generate enhanced outputs. LLM-Blender surpassed individual LLMs and baseline methods across metrics on the MixInstruct dataset, demonstrating substantial performance enhancement.

LLMs provide a unique perspective in SHM through the fusion of text-based information with traditional sensor data. The following outlines how LLMs can enhance SHM through the fusion of data:

- Comprehensive Data Integration: LLMs can gather and analyze a wide range of textual data sources, such as inspection reports, engineering documentation, and research articles related to structural health. LLMs offer a more comprehensive picture of the structural conditions by incorporating textual information.
- Historical Analysis: LLMs can evaluate historical reports and records related to the maintenance and performance of a structure. This historical context enhances real-time sensor data fusion by providing insights into a structure's past behavior, leading to predictive maintenance strategies.
- Anomaly Detection: Anomalies or deviations from normal behavior can be detected with LLMs by evaluating real-time sensor data against historical records. This fusion of data sources enhances the accuracy of anomaly detection and enables earlier identification of potential problems.
- Contextual Understanding: Textual information, for example, reports on past repairs or modifications, provide vital context for interpreting sensor data. Through the analysis of this contextual information, LLMs contribute to an improved understanding of structural health.
- Risk Assessment: LLMs can assess risks by analyzing textual data on factors such as environmental conditions, nearby construction projects, or incidents that might affect the structure's safety. This assessment of risk guides both the decision-making process and the data fusion procedure.
- Cross-Validation: Sensor data can be cross-validated using textual information. For instance, when sensor data indicates structural vibrations, LLMs can verify this by checking for concurrent reports of nearby construction activities.
- Decision Support: Both sensor data and textual information can be synthesized by LLMs to help inform decision-making. As such, LLMs can propose explanations for anomalies based on historical patterns and expert knowledge.

**Table 24**
Data fusion based on AI methods.

| Refs. | Year | Num. | Exp. | Fusion level | AI technique | Description |
|---|---|---|---|---|---|---|
| [413] | 2017 | | ✓ | Data | K-nearest neighbors | A novel sensor data fusion technique is presented by combining feature vectors and K-nearest neighbor machines. |
| [274] | 2016 | ✓ | | Data | Fuzzy inference | A hybrid ART and adaptive fuzzy inference system is proposed as the basis for an intelligent data fusion framework. |
| [54] | 2010 | ✓ | | Data | Hierarchical ensemble | An ensemble hierarchical data fusion scheme is introduced in this study. Hierarchical ensembles are constructed using Dempster–Shafer (DS) and Rotation Forest (RF) theories. |
| [414] | 2021 | ✓ | | Data | Deep convolutional neural network | A novel deep convolutional neural network-based roadway classification tool is presented, which examines its performance when combined with heterogeneous images. |
| [415] | 2020 | ✓ | | Feature | Convolutional neural network semantic image segmentation | Using the damage size estimations from other modules, an online estimate of the structure's remaining useful life is obtained. |
| [275] | 2020 | ✓ | ✓ | Feature | Hybrid Deep Learning | This study develops a practical end-to-end framework integrating physical features embedded in raw data with a hybrid deep learning model, 1-DCNN-LSTM, featuring two algorithms, convolutional neural networks (CNN) and long short term memories (LSTM). |
| [416] | 2021 | ✓ | | Data | DL | Using transfer learning and deep learning, a crack diagnosis framework is proposed that combines a new data-to-imaging approach with DL-aided approaches to automate the diagnosis process. |
| [417] | 2021 | ✓ | ✓ | Data | CNN | This paper proposes a multi-sensor information fusion method based on mechanical vibration propagation characteristics in space for fault classification. |
| [418] | 2023 | ✓ | ✓ | Data | SVM | In the proposed method, conflicting results between sensor data can have a negative impact on classification due to a three-module approach to information fusion. |
| [419] | 2022 | ✓ | | Data | CNN | A novel method for sensor fusion based on image fusion concepts is proposed in this study. |
| [420] | 2019 | ✓ | ✓ | Data | Random projection | Using measured vibration responses, this study develops and verifies a solid framework for the assessment of the structural condition of real-life structures with multiple progressive damages. |

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– Predictive Maintenance: Through the analysis of sensor data and historical records, LLMs can accurately predict maintenance requirements. They can offer suggestions regarding maintenance schedules, leveraging both quantitative sensor data and qualitative textual information.

– Continuous Learning: LLMs can become more effective as they accumulate more information over time. By continuously ingesting and analyzing new textual information, they can refine their understanding of structural health and contribute to integrating data more accurately.

**Table 24** (*continued*).

| | | | | | | |
|---|---|---|---|---|---|---|
| [421] | 2021 | | ✓ | Decision | Bayesian method | Using the fusion of different damage indices and evaluation methodologies, the article demonstrates that a better design of the structural health monitoring system can be implemented. |
| [422] | 2020 | ✓ | ✓ | Decision | SVM | An improved Dempster–Shafer (D–S) evidence theory is combined with multi-classifier support vector machines (SVM) to provide robust risk analysis. |
| [111] | 2021 | ✓ | | Data | PCA | Using electromechanical impedance (EMI) data, a new sensor network-optimized data fusion approach is presented for monitoring the structural health of metallic structures. |
| [27] | 2017 | | ✓ | Data | Bayesian inference | Data from different condition monitoring systems are combined using a two-stage Bayesian inference approach presented in this paper. |
| [423] | 2018 | ✓ | ✓ | Feature | Multiple ML techniques | Using an integrated multisensor fusion-based deep feature learning approach (IMSFDFL), this paper identifies the fault severity in rotating machinery. |
| [424] | 2022 | ✓ | | Data | Neighborhood rough set model | A two-step fusion model is proposed to deal with multiple sources of information and the complexity of the information system. |
| [425] | 2020 | ✓ | | Decision | Multiple DL techniques | This report proposes a tunnel inspection solution for monitoring changes in tunnel linings. |
| [426] | 2015 | | ✓ | Decision | Multi-agent system | In this paper, a multi-agent fusion and coordination system is presented for identifying damage in large structures due to strain distribution and joint failures. |
| [427] | 2020 | ✓ | | Data & Feature | Multiple ML techniques | By combining structural sensors and wearable devices, this study proposed effective methods of estimating crowd flows and loads on pedestrian bridges. |
| [428] | 2021 | ✓ | ✓ | Decision | PCA and ANN | A framework for generating features, reducing data dimensionality, and detecting faults are presented in this paper. |
| [429] | 2018 | ✓ | | Decision | Bayesian Neural Networks | A new methodology for fusing SHM data is proposed to generate prognostic features. |
| [430] | 2023 | ✓ | | Decision | Revised Counter-Propagation Network (RCPN) | An improved method of structural damage identification based on vibration responses are presented in this paper. |
| [431] | 2020 | ✓ | | Data | Naive Bayes | NB-FCN and fully convolutional networks are used in this paper to extract multi-layer features for automatically segmenting cracks and noise. |
| [432] | 2022 | ✓ | | Data | Backpropagation (BP) neural network | The development of a new type of radio frequency identification (RFID) strain sensor, which combines a compact structure with a separate function, is presented. |

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**Table 24** (*continued*).

| | | | | | | |
|---|---|---|---|---|---|---|
| [433] | 2023 | ✓ | | Feature | PCA | Based on sparse sensor arrays and multi-domain-feature fusion, this paper presents a method for identifying quantitative damage in composite structures. |
| [434] | 2018 | ✓ | | Data | Naïve Bayes | For crack detection, this study proposes a DL framework based on an NB-CNN fusion of CNN and Nave Bayes data. |
| [435] | 2013 | ✓ | | Data | Bayesian ML | Analyzing monitoring data and inferring the structural condition state of a cable-stayed bridge using Bayesian logic is illustrated in this paper. |
| [436] | 2007 | ✓ | | Data | Kalman filtering | The aim of this study was to develop a multi-rate Kalman filtering method for monitoring dynamic systems by fusing displacement and acceleration response measurements. |
| [437] | 2012 | ✓ | | Data | Kalman filtering | An integrated vehicle health maintenance system (IVHMS) based on fault detection and feedback is described in this paper. An IVHMS failure risk reduction model that uses fuzzy data fusion was developed. |
| [276] | 2022 | ✓ | ✓ | Data | CNN | The purpose of this paper is to improve damage detection accuracy by combining multiple vibration data (acceleration and strain). |
| [438] | 2021 | ✓ | | Feature | Deep Transfer Learning | To detect earthquake building damage using orthophoto and off-nadir images, this study proposes a multi-modal integrated structure. |
| [65] | 2020 | ✓ | | Data | CNN | The purpose of this research is to discover whether data fusion can improve damage classification through the use of CNNs. |
| [2] | 2021 | ✓ | | Data | PNN | The paper proposes a new intelligent data fusion system that combines PNN and correlation fractal dimensions (CFD). |
| [293] | 2015 | ✓ | ✓ | Decision | Posteriori probability support vector machines (PPSVM) | This paper proposes an intelligent detection method for building structural damage identification using machine learning and data mining techniques. |
| [62] | 2017 | ✓ | ✓ | Data | PCA | A combination of data fusion strategies and pattern recognition algorithms is discussed in the present paper, which can convert large datasets into smaller information pieces and analyze them in real-time. |
| [439] | 2022 | ✓ | | Multi-level | PCA | Multi-level data fusion and anomaly detection techniques are used in this study to detect bridge damage. |
| [56] | 2011 | ✓ | | Decision | PNN | Data fusion techniques, PNNs, and measured modal data are integrated in this paper for damage detection. |
| [440] | 2015 | ✓ | | Data | Probabilistic principal component analysis (PPCA) | This paper proposes a new approach to improve numerical control (NC) machine tool damage identification using data fusion with vibration data. |

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**Table 24** (*continued*).

| | | | | | | |
|---|---|---|---|---|---|---|
| [441] | 2020 | ✓ | | Data | ANN | The purpose of this paper is to present a method for detecting damage to bottom-set gillnets. |
| [442] | 2011 | ✓ | | Data | PNN | A new high-level data fusion model for structural damage detection is presented in this paper. |
| [66] | 2022 | ✓ | | Data | CNN | Using CNNs, this paper discusses how data fusion techniques and data augmentation can be used to improve damage diagnostics |
| [443] | 2023 | ✓ | | Data | PCA | In order to diagnose the condition of concrete arch beams, an optimized deep learning model is integrated with multi-sensor fusion to create a novel hybrid framework. |
| [444] | 2022 | | | Data & Feature | CNN | The proposed method combines multi-level vibroacoustic signals with a one-dimensional convolutional neural network (1D-CNN) to identify centrifugal fan blade damage. |
| [445] | 2020 | ✓ | ✓ | Feature | Parallel convolutional neural network (PCNN) | A novel integrated model is presented using deep learning and multi-sensor feature fusion. |
| [446] | 2020 | ✓ | | Data | Improved CNN | Based on multi-sensor data fusion and improved deep CNNs, a novel intelligent diagnosis method for rotary equipment is proposed. |
| [447] | 2021 | ✓ | ✓ | Decision | CNN | A novel approach is presented in this paper to improve structural damage detection accuracy by using a 1-D CNN and a decision-level fusion algorithm. |
| [448] | 2017 | ✓ | | Multiple levels | DCNN | For fault diagnosis, deep convolutional neural networks (DCNNs) were used as a method of adaptive multisensor data fusion. |
| [449] | 2018 | ✓ | | Decision | Semi-Supervised DL | Our goal in this paper is to develop a semisupervised deep-learning scheme for diagnosing multiple defects in an induction machine gearbox, including simultaneous ones. |

As previously discussed, LLMs are primarily applied to text inputs. However, it is worth noting that there are limitations to using LLMs for signal-based data. Exploring the potential of applying LLMs in SHM with signal inputs represents a promising area for future research that researchers can consider.

## 7. Comparative overview of significant papers

In the following, we provide an overview of the most influential and important papers that employ data fusion techniques for application in SHM. To facilitate a meaningful comparison, we devised a generic framework that enables a side-by-side assessment of the presented papers to assess the research quality, focus, maturity, and depth. The development of the criteria stems from a meticulous examination of the existing literature, including research papers and review articles in the field of data fusion and SHM. The selection of the criteria for evaluating the papers in this work was guided by a combination of insights gained from reviewing a significant number of research papers. Drawing from the review of the above 489 papers, we identified the most relevant and impactful aspects that contribute to the assessment of research quality, methodology, and applicability within the context. Our objective is to provide readers with a clear and holistic understanding of the diverse papers in the field by using a comprehensive comparison framework. The overarching structure we have devised for evaluation encompasses the most important elements of this assessment process. This approach ensures that readers are equipped with a well-rounded perspective when selecting papers for further reading and reference. The use of this framework enables readers to assess and compare various papers quickly based on standardized criteria. Using this approach, researchers can identify relevant papers that are aligned with their interests and research objectives more quickly. Below, we provide details of the criteria and the rationale behind their selection that served as the basis for the comparative assessment of original and review papers, respectively.

- **Criteria for original papers:**
  - Experimental validation (EV): We acknowledge the significance of experimental verification in affirming the validity and practical applicability of research findings. This criterion allows us to distinguish studies that have undergone rigorous testing using real-world data from those relying solely on simulated or benchmark data.
    - Yes (Y): The study was verified through experimental data.

    - No (N): The study was verified through simulated or benchmark data.
  - Comparison with other methods (CO): A vital aspect of evaluating new methods is their performance relative to existing approaches. This criterion was chosen to assess the extent to which authors benchmark their proposed methods against established alternatives, thus ensuring a fair evaluation of innovation and effectiveness.
    - Yes (Y): The proposed method was compared with the other methods.
    - No (N): The proposed method was not compared with the other methods.
  - Noise analysis (NA): Noise represents an inherent challenge in real-world sensor data. By considering the influence of noise, the robustness and reliability of methods in mitigating the impact of noise on response signals can be evaluated, enhancing the credibility of the research findings.
    - Yes (Y): The method considers the effects of noise on the response signals.
    - No (N): The method does not consider the effects of noise on the response signals.
  - Proposed type of method (PT): The categorization of methods into high-level (advanced) and low-level (classical) acknowledges the evolving landscape of SHM techniques. This criterion provides insights into whether authors are leveraging cutting-edge ML and DL methods or relying on traditional approaches.
    - High (H): The data fusion-based SHM system is based on advanced methods such as ML and DL.
    - Low (L): The data fusion-based SHM system is based on classical methods.
  - Environmental and Operational Condition (EOC) analysis (EA): Environment and operational conditions can have a significant effect on SHM outcomes. This criterion assesses whether authors take these influences into account, thereby reflecting the methods' real-world applicability and relevance.
    - Yes (Y): The method considers the effects of EOCs on the response signals.
    - No (N): The method does not consider the effects of EOCs on the response signals.
  - Comparison to other models (CP): A comparative analysis provides context for evaluating a method's unique contributions. This criterion evaluates whether authors compare their models to other approaches, enabling insights into the relative strengths and weaknesses of different methods.
    - Yes (Y): The proposed method is compared to other models.
    - No (N): The proposed method is not compared to other models.
- **Criteria for review papers:**
  - Comprehensiveness of the subject (CS): A review's value lies in its ability to offer a comprehensive overview of the subject matter. This criterion ensures that reviews encompass all relevant taxonomies, techniques, applications, advantages, and disadvantages, serving as a valuable reference for readers seeking a holistic understanding.
    - Complete (C): The review presents all the subject's taxonomies, techniques, applications, advantages, and disadvantages.
    - Incomplete (IC): The review does not present all the subject's taxonomies, techniques, applications, advantages, and disadvantages.
  - Review tables (RT): Comparative tables offer a convenient visual reference for readers to compare various attributes across different papers. The presence of such tables enhances the readers' accessibility to essential information, facilitating an enhanced understanding of the content.
    - Yes (Y): The review articles include comparative tables of the relevant papers.
    - No (N): The review articles do not include comparative tables of the relevant papers.
  - Challenges of the subject (ChS): Acknowledging challenges is essential for fostering innovation. This criterion underscores the importance of discussing existing obstacles and stimulating further research efforts.
    - Yes (Y): The review discusses the challenges of the subject.
    - No (N): The review does not discuss the challenges of the subject.
  - Future aspects of the subject (FA): By considering future trends, reviews can guide researchers and practitioners towards emerging directions. This criterion ensures that reviews offer insights into the subject's potential trajectory.
    - Yes (Y): The paper presents the future trends of the subject.
    - No (N): The paper does not present the future trends of the subject.

In Table 25 and Table 26, we comprehensively review the current original and review papers on data fusion-based SHM, respectively.

## 8. Application of data fusion in smart cities

The integration of digital technology in urban areas is commonly known by the term "Smart City". The aim of this concept is to optimize the operations and services of cities by collecting digital data from a diverse range of sensing technologies and their integration into the IoT. In a smart city, technology, government, and society are connected to enable the following characteristics: a smart economy, smart living, smart mobility, smart governance, smart people, and a smart environment. Data fusion is key to the high level of analytics required for the processing of smart city data encompassing areas including the IoT [483], Data Mining [484], Machine Learning [485], Communication Technology [486] and Big Data [487]. The fast transformation of urban cities drives a strong research interest in using data fusion techniques for smart city data analytics. Below, we provide an overview of the significant components of a smart city:

- **Smart living**: Smart living strives to improve the livability of urban regions and includes the subdomains Smart Homes, Smart Health, and Smart Community.
- **Smart urban area**: Smart urban area management involves managing urban regions using Information and Communications Technology (ICT) and includes Smart Governance, Smart Urban Planning, and Smart Building.
- **Smart environment**: A smart environment encompassing internal and external regions of a city and focuses on areas such as Urban City Modeling, Landscape Monitoring, and Waste Management.

**Table 25**
Overview of recent original papers based on proposed criteria.

| Refs. | Method | NA | EV | CO | PT | EA | CP |
|---|---|---|---|---|---|---|---|
| Dhanaraj et al. [12] | Deep neural network (DNN) | N | Y | N | H | N | N |
| Jaramillo et al. [27] | Data level | N | Y | N | L | N | N |
| Fawzy et al. [92] | IoT-based spatiotemporal method | Y | Y | N | H | N | N |
| Zhao et al. [207] | Signal level | Y | Y | N | L | N | N |
| Song et al. [208] | Signal level | Y | Y | Y | L | N | N |
| Sun et al. [209] | Signal level | Y | Y | Y | H | N | N |
| Li et al. [210] | Signal level | Y | Y | Y | H | N | N |
| Malchi et al. [93] | Fuzzy neural network | N | N | Y | H | N | N |
| Bao et al. [109] | D–S evidence theory | Y | Y | Y | L | Y | N |
| Li et al. [88] | Fuzzy analytical hierarchy | N | Y | N | H | N | N |
| Singh et al. [111] | Signal level | N | N | Y | H | N | N |
| Lu et al. [121] | Signal level | N | N | Y | L | N | N |
| Schmitt et al. [175] | Signal level | N | N | Y | L | N | N |
| Goshvarpour and Goshvarpour [198] | Feature level | N | Y | Y | L | N | Y |
| Wan et al. [176] | Deep transfer learning | Y | Y | Y | H | N | Y |
| Cai et al. [200] | Feature level | N | Y | N | L | N | Y |
| Jeng and Chen [201] | Feature level | N | Y | Y | L | N | Y |
| Conde et al. [177] | Signal level | Y | Y | Y | H | N | N |
| Sun et al. [202] | Feature level and decision level | Y | Y | Y | H | N | N |
| Lip and Ramli [203] | Decision level | Y | Y | Y | H | N | Y |
| Grochala and Kedzierski [178] | Signal level | N | Y | Y | H | N | N |
| Wang et al. [179] | Signal level | Y | Y | Y | L | N | N |
| Ramos et al. [180] | Bayesian data fusion techniques | N | N | Y | L | N | Y |
| Dos Santos et al. [181] | DNN and Adaptive Monte Carlo Localization | N | N | N | H | N | N |
| Pradhan et al. [182] | Wavelet transform technique | N | Y | Y | H | N | N |
| Ben Atitallah et al. [183] | D-S theory | Y | Y | Y | H | N | N |
| Torres et al. [192] | IoT | Y | Y | Y | H | N | N |
| Dasarathy [188] | Decision level | N | Y | N | L | N | N |
| Khan et al. [94] | CNN | N | Y | Y | H | N | N |
| He et al. [95] | Wavelet transform | N | N | Y | H | N | N |
| Daniel et al. [106] | Signal level | N | N | Y | H | N | Y |
| Li et al. [107] | Signal level | N | Y | Y | H | Y | N |
| Jiang et al. [50] | Probabilistic neural network (PNN) | N | Y | Y | H | N | N |
| Singh et al. [43] | Signal level | N | Y | Y | L | N | Y |
| Dabetwar et al. [66] | Deep Neural Network (DNN) | N | N | N | H | N | N |
| Ihnaini et al. [29] | Feature level | N | Y | N | L | N | N |
| He et al. [30] | Digital twin | N | N | N | H | N | N |
| Shi et al. [31] | Data level | Y | Y | Y | L | N | N |
| Jiang et al. [34] | RNN | N | Y | Y | H | N | N |
| Jiang et al. [35] | Distance-probability classification (DPC) | N | Y | Y | H | N | N |
| Patil and Kumar [36] | CNN | N | Y | Y | H | N | N |
| Yang et al. [33] | Spatial-Temporal Adaptive Reflectance Fusion Model (STARFM) | N | Y | Y | L | N | N |
| Du et al. [453] | ML | N | Y | Y | H | N | Y |
| Zhang et al. [85] | SVM, CNN and D-S evidence theory | N | N | N | H | N | N |
| Barman et al. [32] | Bayesian data fusion | N | N | N | L | N | Y |
| Izadi et al. [28] | Fuzzy-based data fusion | N | Y | Y | H | N | N |
| Luwei et al. [454] | Feature level | N | Y | N | H | N | N |
| Muzammal et al. [25] | Signal level | N | Y | N | L | N | N |
| Arora and Mahajan [254] | Decision level | N | Y | Y | L | N | Y |
| Nallagonda et al. [255] | Decision level | N | Y | Y | L | N | Y |
| Soltane and Mimen [256] | Decision level | N | Y | Y | H | N | Y |
| Yan et al. [257] | Decision level | Y | N | Y | L | N | Y |
| Chakraborty and Stolinski [272] | Signal level | Y | Y | Y | L | N | Y |
| Sharif Khodaei and Aliabadi [273] | Decision level | Y | Y | Y | L | N | Y |
| Sun et al. [274] | Signal level | Y | Y | Y | H | N | Y |
| Zhang et al. [276] | Decision level | Y | Y | Y | L | N | Y |
| Teng et al. [277] | CNN | Y | Y | Y | H | N | Y |
| Dang et al. [275] | Feature level | Y | Y | Y | H | N | Y |
| Downey et al. [278] | Feature level | Y | Y | Y | L | N | Y |
| Chakraborty et al. [279] | Feature level | Y | Y | Y | L | N | Y |
| Yang et al. [217] | Decision level | N | N | N | L | N | N |
| Sadoughi et al. [280] | Signal level | Y | Y | Y | H | N | Y |
| Smyth and Wu [51] | Multi-rate Kalman filtering | Y | N | N | H | N | N |
| Bramon et al. [281] | Signal level | Y | N | N | L | N | N |
| Malawade et al. [282] | Signal level | Y | N | N | L | N | N |
| Çavdar et al. [225] | CNN and D–S evidence theory | Y | N | Y | H | N | N |

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– **Smart industry**: Smart industry applications primarily employ information collected from physical sensor systems and include Smart Manufacturing, Smart Maintenance, and Smart Agriculture.

– **Smart economics**: Smart economics involves commercial enterprises on the urban city scale and includes the three essential parts Smart Commerce, Smart Supply Chain, and Smart Tourism.

**Table 25** (*continued*).

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Cuzzocrea et al. [226] | D–S evidence theory | Y | Y | Y | L | N | N |
| Li et al. [227] | CNN | Y | Y | Y | H | N | N |
| Uddin et al. [228] | RNN | Y | Y | Y | H | Y | Y |
| Liu et al. [229] | Fuzzy logic theory | Y | Y | Y | H | N | N |
| Bigdeli et al. [409] | SVM | N | Y | Y | H | N | Y |
| Giacinto et al. [410] | Signal level | N | N | N | H | N | N |
| Chen and Jahanshahi [412] | CNN and Naive Bayes | Y | Y | Y | H | N | Y |
| Vitola et al. [413] | KNN | Y | Y | N | H | N | Y |
| Zhou and Song [414] | DL | Y | Y | N | H | N | Y |
| Aria et al. [415] | DL | Y | Y | N | H | N | Y |
| Hasan et al. [416] | ML | Y | Y | N | H | N | Y |
| Wang et al. [455] | CNN | Y | Y | N | H | N | Y |
| Kannan et al. [418] | Signal level | Y | Y | N | L | N | Y |
| Cinar [419] | ML | Y | Y | N | H | N | Y |
| Makki Alamdari et al. [420] | Frequency domain decomposition | Y | Y | Y | H | N | Y |
| Li et al. [456] | Frequency domain decomposition | Y | Y | Y | H | N | Y |
| Pan et al. [422] | Signal level | N | Y | Y | L | N | Y |
| Liu et al. [423] | Deep feature learning | N | Y | Y | H | N | Y |
| Attard [425] | Computer vision | N | Y | Y | H | N | Y |
| Mustapha et al. [427] | ML | N | Y | Y | L | N | Y |
| Cao and Yunusa-Kaltungo [428] | Signal level | N | Y | Y | L | N | Y |
| Eleftheroglou et al. [429] | Signal level | N | Y | N | L | N | N |
| Fu and Li [430] | ML | N | Y | N | H | N | N |
| Li et al. [431] | CNN and Naive Bayes | Y | Y | N | H | N | N |
| Wan et al. [432] | Signal level | Y | Y | N | L | N | N |
| Wang et al. [439] | DL | Y | Y | N | H | N | Y |
| Tang et al. [433] | Feature level | Y | Y | N | L | N | N |
| Yuqing et al. [440] | Signal level | Y | N | N | L | N | N |
| Jiang et al. [442] | PNN | Y | Y | N | H | N | N |
| Yu et al. [443] | DL | Y | Y | N | H | N | Y |
| Zhang et al. [444] | Signal level | N | Y | N | L | N | Y |
| Xu et al. [445] | DL | Y | Y | N | H | N | Y |
| Wang et al. [457] | DL | Y | Y | N | H | N | Y |
| Teng et al. [277] | CNN | Y | Y | N | H | N | Y |
| Jing et al. [448] | Deep CNN | Y | Y | N | H | N | Y |
| Razavi-Far et al. [449] | Semi-supervised deep learning | Y | Y | N | H | N | Y |
| Zonta et al. [458] | Signal level | Y | Y | N | L | N | N |
| Smyth and Wu [51] | Kalman filtering | Y | Y | N | H | N | N |
| Rodger [437] | Kalman filtering | N | Y | N | H | N | N |
| Abdi and Jabari [438] | Deep transfer learning | Y | Y | N | H | N | N |
| Chen and Jahanshahi [412] | CNN and Naive Bayes | Y | Y | N | H | N | N |
| Jaramillo et al. [27] | Bayesian inference | Y | Y | N | H | N | Y |
| Liang and Yuan [426] | Signal level | N | Y | Y | L | N | Y |
| Zhou et al. [424] | ML | N | Y | Y | H | N | Y |
| Li et al. [246] | D–S evidence theory | Y | N | Y | H | N | N |
| Sarkar et al. [247] | D–S evidence theory | Y | Y | Y | H | N | N |
| Hao et al. [233] | Signal level | Y | Y | Y | H | N | Y |
| Wang et al. [237] | Weighted adaptive Kalman filtering | Y | Y | Y | H | N | Y |
| Li and Wang [399] | Signal level | N | Y | N | L | N | N |
| Li et al. [52] | D–S evidence theory | Y | N | Y | H | N | N |
| Wang et al. [400] | Signal level | Y | N | Y | L | N | N |
| Lu and Michaels [53] | Feature level | Y | Y | Y | L | N | N |
| Xiao and Liu [401] | Signal level | Y | Y | Y | L | N | N |
| Starzacher and Rinner [405] | Feature level | Y | Y | N | L | N | N |
| Wang et al. [402] | Fuzzy logic | Y | Y | Y | H | N | N |
| Cao et al. [406] | SVM | Y | Y | Y | H | N | N |
| Alyannezhadi et al. [403] | Signal level | Y | Y | Y | H | N | N |
| Ghosh et al. [407] | CNN | Y | Y | Y | H | N | N |
| Zhao et al. [54] | Hierarchical ensemble | N | Y | Y | H | N | Y |
| Pouteau and Stoll [404] | SVM | Y | Y | N | H | N | N |
| Ferrari et al. [60] | Rate Kalman filtering method | N | Y | Y | L | N | Y |
| Jiang et al. [56] | PNN | Y | N | Y | H | N | Y |
| Mishra et al. [61] | Decision level | N | Y | N | L | N | N |
| Guo and Xu [63] | D-S evidence theory | Y | N | N | L | N | N |
| Dabetwar et al. [65] | DNN | Y | Y | Y | H | N | Y |
| Ding et al. [64] | D-S evidence theory | Y | Y | Y | H | N | Y |
| Ye et al. [315] | Signal level | N | Y | N | L | N | N |
| Xu et al. [367] | CNN | N | Y | N | H | N | N |

(*continued on next page*)

– **Smart human mobility**: Smart human mobility aims at improving the mobility of the urban population and covers aspects such as Human Mobility Understanding, Smart Location-Based Services, and Smart Transportation Systems.

**Table 25** (*continued*).

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Challa et al. [395] | SVM | N | Y | N | H | N | N |
| Kolanowski et al. [397] | Elman neural networks | N | Y | N | H | N | N |
| Zhong et al. [398] | Semi-supervised learning method | N | Y | N | H | N | N |
| Azamfar et al. [459] | CNN | N | Y | N | H | N | N |
| Wang et al. [460] | CNN | N | Y | N | H | N | N |
| Wei et al. [461] | Signal level | N | Y | N | L | N | N |
| Cao et al. [462] | Signal level | Y | Y | Y | L | N | N |
| Shi et al. [463] | ML | Y | Y | Y | H | N | N |
| Buchaiah and Shakya [464] | Signal level | N | Y | Y | L | N | N |
| Fahmy et al. [396] | SVM | N | Y | N | H | N | N |
| Völker and Shokouhi [318] | Signal level | N | Y | N | L | N | N |
| Santos et al. [62] | Signal level | Y | Y | Y | L | N | Y |
| Banerjee and Das [57] | Support Vector Machine (SVM) and Short Term Fourier Transform (STFT) techniques | N | Y | Y | H | N | Y |
| Vanniamparambil et al. [58] | Digital image correlation (DIC) | N | Y | N | H | N | N |
| Grande and Imbimbo [59] | Decision level | Y | N | N | L | N | Y |
| Vandone et al. [26] | Signal level | N | Y | N | L | N | N |
| Wang et al. [465] | Feature level | N | Y | N | L | N | N |
| Vemuri et al. [23] | DNN | N | N | N | H | Y | N |
| Carnevale et al. [24] | Data level | N | Y | N | L | N | Y |
| Jararweh et al. [466] | Internet of things (IoT) | N | Y | Y | H | Y | N |
| Amorim et al. [22] | Data level | Y | Y | N | L | N | N |
| Zhou et al. [21] | Extended Kalman filter (EKF) | N | Y | N | H | N | N |
| Fu and Jiang [2] | PNN | Y | N | N | H | N | Y |
| Vitola et al. [413] | k-NN | N | Y | N | H | N | Y |
| Zhu et al. [467] | LSTM | N | Y | N | H | N | Y |
| Xin et al. [468] | Bayesian fusion theory | Y | Y | N | H | N | N |
| Li et al. [381] | Improved gru network | Y | Y | N | H | N | N |
| Meng et al. [376] | CNN | Y | Y | N | H | N | N |
| Zou et al. [377] | Feature level | Y | Y | N | H | N | N |
| Han et al. [6] | Signal level | Y | Y | N | L | N | N |
| Bhagat et al. [385] | Signal level | N | Y | N | L | N | N |
| Yao et al. [380] | Signal level | N | Y | N | L | N | N |
| Chen and Jahanshahi [412] | Decision level | Y | Y | N | L | N | N |
| Jing et al. [448] | DCNN | N | Y | N | H | N | Y |
| Liang et al. [90] | DNN | N | Y | Y | H | N | N |
| Singh et al. [111] | ML | N | Y | N | H | N | N |
| Barman et al. [32] | Bayesian approach | Y | N | N | L | N | Y |
| Broer et al. [5] | Feature level fusion | Y | Y | N | L | N | Y |
| Eleftheroglou et al. [469] | Feature method | N | Y | N | L | N | N |
| Ding et al. [64] | D-S evidence theory | Y | Y | N | L | N | N |
| Azamfar et al. [459] | CNN | Y | Y | Y | H | N | N |
| Wang et al. [460] | CNN | Y | Y | Y | H | N | Y |
| Wei et al. [461] | Feature method | N | Y | Y | L | N | N |
| Cao et al. [462] | Feature method | Y | Y | N | L | N | Y |
| Buchaiah and Shakya [464] | Feature method | N | Y | Y | L | N | N |
| Saffari et al. [37] | Bayesian fusion method | N | Y | Y | L | N | Y |
| Mahajan et al. [45] | Fuzzy Logic | N | Y | Y | H | N | N |
| Dempsey et al. [46] | Decision level | N | Y | Y | L | N | N |
| Ou and Li [47] | Data level | Y | Y | N | L | Y | N |
| Joubert and Bihan [48] | Data level | N | Y | N | L | N | N |
| Chun et al. [49] | DNN | N | Y | Y | H | N | N |
| Shi et al. [463] | CNN | Y | Y | Y | H | N | Y |

– **Smart infrastructure**: Smart infrastructure provides the public with intelligent structures and systems such as buildings, public facilities, communication systems, and distribution infrastructure for resources, including gas, electricity, and water. Subdomains include Smart Infrastructure Monitoring, Smart Grid, Smart Facility, Smart Energy, and Smart Communication.

In Table 27, we review recent surveys published on the application of data fusion techniques for smart city analytics evaluating multi-aspect efficiencies.

## 9. Data fusion challenges

Major progress has been achieved in the technological advancement of data fusion systems. However, critical bottleneck issues still exist, compromising the efficiency and acceptance of this technology. Challenges mainly arise from the large variety of sensor systems and the heterogeneity of collected data. Below, we outline the primary challenges faced by current data fusion techniques.

– **Data imperfection**: The information recorded from sensors can be incomplete, imprecise, and polluted with noise. Data imperfection can severely compromise extracting valuable and precise information using data fusion techniques. To improve information quality, advanced mathematical tools must be implemented.
– **Data inconsistency**: Data inconsistency occurs when the information from multiple sources does not match. Inconsistent data appears as outlier information impacting the performance of data fusion techniques.
– **Data confliction**: Data confliction is often the source of clashing evidence in belief functions or D–S theory. In such cases, a representation error occurs when contradictory evidence is erroneously fused.
– **Data alignment or data registration**: Data captured from various sensor systems must be aligned in a unifying structure before fusing. The lack of such practice, called data alignment or data registration, often results in over- or under-confidence.
– **Data correlation**: Data correlation often occurs in distributed networks when the same data set is fused more than once. If not

**Table 26**
Overview of recent review papers based on proposed criteria.

| Refs. | CS | RT | ChS | FA |
|---|---|---|---|---|
| Liu et al. [20] | IC | N | N | Y |
| King et al. [470] | IC | Y | Y | N |
| Kulkarni and Rege [195] | IC | Y | Y | Y |
| Zhao et al. [251] | IC | Y | Y | Y |
| Nweke et al. [471] | IC | Y | N | N |
| Lahat et al. [472] | C | Y | Y | Y |
| Mohammad-Djafari [294] | IC | N | N | N |
| Himeur et al. [473] | IC | Y | Y | Y |
| Qi et al. [474] | IC | Y | Y | Y |
| Qi et al. [474] | IC | Y | Y | Y |
| Tsanousa et al. [475] | IC | Y | N | Y |
| Himeur et al. [476] | C | Y | Y | Y |
| Kashinath et al. [1] | IC | Y | N | Y |
| Wang et al. [391] | C | Y | Y | Y |
| Dadgar et al. [91] | IC | Y | Y | N |
| Zhang et al. [211] | C | Y | Y | Y |
| Azam et al. [212] | IC | Y | Y | Y |
| Muhammad et al. [196] | IC | Y | N | N |
| García-Macías and Ubertini [356] | IC | N | N | N |
| Kannan et al. [199] | IC | Y | N | N |
| Solanky and Katiyar [197] | IC | Y | N | N |
| Yang et al. [89] | IC | Y | Y | Y |
| Adamopoulos and Rinaudo [42] | IC | Y | N | N |
| Castanedo [204] | IC | Y | N | N |
| Sinha et al. [205] | IC | Y | N | N |
| Liu [383] | IC | Y | N | N |
| Bala et al. [206] | IC | Y | N | N |
| Mu et al. [74] | IC | N | N | N |
| Reichard et al. [44] | IC | Y | N | N |
| Duan et al. [79] | IC | Y | Y | Y |
| Chen et al. [76] | IC | Y | Y | N |
| Li and Wang [194] | C | Y | Y | Y |
| Dalla Mura et al. [77] | IC | Y | Y | Y |
| Ghassemian [78] | C | Y | Y | Y |
| Alam et al. [68] | C | Y | Y | Y |
| Broer et al. [69] | IC | Y | Y | N |
| Ding et al. [70] | C | Y | Y | Y |
| Nsengiyumva et al. [73] | C | Y | Y | Y |
| Zhang et al. [16] | IC | Y | N | Y |
| Borràs et al. [477] | IC | Y | N | N |
| Meng et al. [17] | IC | Y | Y | Y |
| Gettelman et al. [19] | IC | Y | N | Y |
| Karagiannopoulou et al. [478] | IC | Y | Y | Y |
| Wu and Jahanshahi [71] | C | Y | Y | N |
| Joshi et al. [8] | IC | Y | N | N |
| Gao et al. [3] | IC | Y | N | N |
| Becerra et al. [9] | C | Y | N | Y |
| Kolar et al. [10] | C | Y | N | N |
| Li et al. [4] | IC | Y | N | N |
| Kralovec and Schagerl [75] | IC | N | N | N |
| Nweke et al. [471] | C | Y | N | Y |
| Lahat et al. [472] | IC | N | Y | N |
| Himeur et al. [473] | C | Y | Y | Y |
| Qi et al. [474] | IC | Y | N | Y |
| Liu et al. [18] | C | Y | Y | N |
| Kong et al. [7] | C | N | N | Y |
| Zheng [479] | C | N | N | N |
| Ghamisi et al. [14] | IC | N | Y | Y |
| Wang et al. [391] | IC | N | N | N |
| Gravina et al. [480] | C | Y | Y | Y |
| Krishnamurthi et al. [72] | IC | N | N | N |
| Fung et al. [481] | IC | N | N | N |
| Salcedo-Sanz et al. [368] | C | Y | Y | Y |
| Duan et al. [79] | IC | N | N | N |
| Zhang et al. [482] | C | Y | Y | Y |
| Li et al. [193] | C | Y | Y | Y |

**Table 27**
Summary of recent works on data fusion applications in the smart city.

| Refs. | Review focus | Description |
|---|---|---|
| Lau et al. [488] | Application | In this study, a multi-perspective classification for data fusion techniques is provided. An overview of the different domains of smart city applications is given, and future challenges and possible directions for future work are investigated. |
| Tsanousa et al. [475] | Application | This survey proposes a guideline for an analytic scheme for manufacturing prognosis. The paper provides an overview of data fusion, sensors, and intelligent manufacturing and identifies weaknesses and gaps in future research goals. |
| Himeur et al. [476] | Application and theory | This paper introduces a well-designed taxonomy to overview existing data fusion frameworks. AI models and data fusion techniques are analyzed for image analysis, and data fusion applications for intelligent monitoring are discussed. |
| Alam et al. [68] | Application | This survey investigates mathematical methods in specific IoT environments. Opportunities and challenges for each method are explored, and the benefits of data fusion and IoT in smart city applications and autonomous vehicles are summarized. |
| Raghavan et al. [489] | Application | In this research, the limitations of current data fusion methods in a smart city are identified. A new model is proposed that can deal with current technical challenges facilitating the analysis of IoT data in smart cities. |

eliminated, correlated data can compromise the effectiveness of a fusion strategy with biased estimation.

– **Data heterogeneity**: Different sensor systems aim at capturing diverse data types. Such multifaceted data sources result in the heterogeneity of the captured data set.
– **Fusion location**: Information can be fused at a central or a local node. While the former fusion type involves high bandwidth and time costs, the latter reduces communication costs through reduced information accuracy due to the data loss of local fusion. There is a trade-off between fusion cost and quality.
– **Dynamic fusion**: In real-time application environments, a significant amount of information is transferred dynamically in a time-varying system. Such a dynamic environment substantially increases the complexity of data fusion.

The challenges of data fusion techniques, especially in real-world settings, involve addressing potential difficulties in integrating diverse and noisy data sources. Uncertainties from measurement errors and complexity can impact fused results' reliability. Challenges also arise from handling dynamic environments, adapting to different domains, validating methods without standardized benchmarks, and ensuring transparency in complex AI-driven techniques. Overcoming these challenges is crucial to effectively apply data fusion in practical scenarios, enhancing its reliability and usability across various dynamic environments.

## 10. Future trends

To overcome the challenges outlined in Section 9, in the following, we identify potential research directions guiding future research efforts to exploit the full potential of current data fusion techniques and to develop new approaches for data fusion-based SHM. First, research should be expanded on the application of AI in data fusion-based SHM. The strength of AI algorithms to deal with nonlinearity in mapping features to target space facilitates the development of more robust data fusion-based SHM techniques. Supervised learning models such as SVM and Random Forest can produce maps in high-dimensional space to represent information produced by complex functions. Second, developing highly complex data fusion models, such as large-scale learning methods, should be further pursued. Such complex models should be based on DL algorithm strategies combining supervised and unsupervised models in a hierarchical order for training more robust data fusion algorithms. Third, fusion models integrated into IoT networks may suffer from data leakage. Hence, rigorous security features must be developed and embedded in fusion algorithms to ensure the preservation of information privacy in the fusion process. Further, the central hardware device responsible for performing the fusion must be protected against possible attacks. As such, responsible data fusion practice demands developing methods with high security and privacy protection features.

As mentioned above, the future of data fusion is likely to involve the development of new methods and technologies that can handle increasingly large and complex data sources and enable more autonomous, dynamic, and interactive data fusion. Some future trends in data fusion include privacy-preserving data fusion, multi-modal data fusion, and interactive data fusion. Table 28 provides a detailed table with additional information about each future trend in data fusion.

## 11. Conclusions

This paper comprehensively reviews state-of-the-art data fusion methods for the performance optimization of structural health monitoring (SHM) systems. Details of the most famous traditional data fusion methods are presented and novel strategies supported by artificial intelligence (AI) are discussed. For each fusion method, this article summarizes the advantages and disadvantages of their application to SHM and provides examples of associated research studies. Furthermore, an extensive comparison of the most significant papers in data fusion-based SHM is provided based on a proposed set of criteria for original and review articles. Finally, the remaining challenges are analyzed, and future research trends on aggregating data efficiently to facilitate robust decision-making are outlined.

The presented systematic literature study reveals a prominent trend toward the application of deep learning (DL) models for data fusion. While the benefits of traditional data fusion techniques are substantial and cannot be overlooked, this trend recently prompted the development of new models taking advantage of both conventional and advanced techniques in hybrid models. Such models can be used in multi-objective tasks where, first, a DL model is used to learn and fuse high-level features extracted from data (images and signals), and then, the known features are fed into models, such as ML algorithms, to solve a classification, regression, or anomaly detection task.

The selection of data fusion techniques for a specific problem is contingent upon aspects such as data type and the nature of the problem, rendering a general recommendation unfeasible. Nevertheless, we strongly encourage readers to take advantage of the knowledge presented in this paper when selecting appropriate data fusion strategies for their unique applications. By delving into the conceptual understanding, benefits, drawbacks, applications, and analogous works associated with these methods, readers can aptly discern and opt for the most fitting approaches tailored to their needs.

Building upon the insights acquired from the authors' research efforts and their contributions to this paper, we encourage readers to engage in a thorough exploration of data fusion, with a particular emphasis on deep learning methodologies. The focus centers on the optimization of efficiency, time, and cost. Specifically, for readers with

**Table 28**
Future trends in data fusion.

| Future trends | Description | Example applications |
|---|---|---|
| Machine learning | Using machine learning algorithms to learn patterns and relationships in complex and high-dimensional data to enable more accurate and efficient data fusion. | – Combining data from multiple sensors on a self-driving car to improve object detection and tracking.<br>– Combining data from multiple medical imaging modalities to improve disease diagnosis and treatment. |
| Integration of data from multiple domains | Combining data from different domains, such as social media and traditional data sources, to generate more accurate and comprehensive insights. | – Combining social media data with weather and traffic data to predict traffic congestion.<br>– Combining satellite imagery with demographic data to identify areas at risk of poverty and social exclusion. |
| Real-time data fusion | Combining data from multiple sources in real-time to provide timely and actionable insights, which is particularly important in the Internet of Things (IoT) context. | – Combining data from multiple IoT devices to optimize energy usage in smart buildings.<br>– Combining data from multiple sensors on a wearable device to monitor a patient's health in real-time. |
| Ethical and legal frameworks | Developing ethical and legal frameworks for data fusion to ensure the responsible use of data, including privacy, security, and bias considerations. | – Developing guidelines for the responsible use of facial recognition technology to minimize the risk of bias and privacy violations.<br>– Developing policies for the responsible sharing of medical data to ensure patient privacy and confidentiality. |
| Heterogeneous data fusion | Developing methods to handle the heterogeneity and diversity of data from multiple sources, including different data types and formats. | – Combining data from text, images, and video to generate multimedia summaries of events.<br>– Combining data from different medical devices with other data formats to create a comprehensive patient record. |
| Collaborative data fusion | Developing methods to enable collaborative data fusion, where multiple parties with different data sources can combine their data to generate more comprehensive insights. | – Combining data from various police departments to identify patterns of criminal activity across jurisdictions.<br>– Combining data from multiple companies in the supply chain to optimize logistics and reduce waste. |
| Context-aware data fusion | Developing methods to incorporate contextual information, such as location, time, and user preferences, to improve the accuracy and relevance of data fusion results. | – Combining data from sensors in a smart city to optimize transportation and energy usage based on current conditions.<br>– Combining data from wearable devices with location data to personalize fitness and wellness recommendations. |
| Explainable data fusion | Developing methods to enable the interpretation and explanation of data fusion results to improve transparency and trust. | – Developing visualization tools to enable users to explore and understand data fusion results.<br>– Developing methods to quantify the contribution of different data sources to data fusion results. |
| Privacy-preserving data fusion | Developing methods to combine data from multiple sources while preserving the privacy of individual data sources. | – Combining medical data from different hospitals while preserving patient privacy.<br>– Combining financial data from different banks while preserving customer privacy. |
| Autonomous data fusion | Developing methods to enable autonomous data fusion, where algorithms automatically select and combine data from multiple sources without human intervention. | – Autonomous selection and combination of data from multiple sensors on a spacecraft to monitor space weather.<br>– Autonomous selection and combination of data from multiple social media platforms to detect and track public opinion. |
| Dynamic data fusion | Developing methods to handle data that changes over time, including changes in data sources, data quality, and data availability. | – Combining real-time weather data with historical weather data to improve weather forecasting.<br>– Combining data from different generations of medical imaging technology to monitor disease progression over time. |
| Ontology-based data fusion | Developing methods to use ontologies to represent and reason about the semantics of data from multiple sources, enabling more accurate and meaningful data fusion. | – Combining data from different sensor networks to detect and monitor natural disasters.<br>– Combining data from other databases enables cross-domain search and analysis. |
| Multi-level data fusion | Developing methods to combine data at multiple levels of abstraction, including raw sensor data, feature-level data, and high-level semantic data, to enable more comprehensive data fusion. | – Combining raw sensor data with feature-level data and semantic data to enable human-like activity recognition.<br>– Combining data from different levels of medical imaging data to improve diagnosis and treatment. |
| Multi-modal data fusion | Developing methods to combine data from multiple modalities, such as text, image, and speech data, to enable more comprehensive data fusion. | – Combining text, image, and speech data from social media to identify and track public opinion.<br>– Combining data from different medical modalities to improve disease diagnosis and treatment. |
| Federated data fusion | Developing methods to enable data fusion across multiple, decentralized data sources while preserving the privacy and security of individual data sources. | – Combining data from multiple hospitals to improve disease diagnosis and treatment while preserving patient privacy.<br>– Combining data from multiple companies to optimize supply chain logistics while preserving proprietary information. |
| Human-in-the-loop data fusion | Developing methods to enable human experts to provide feedback and guidance to data fusion algorithms to improve the accuracy and relevance of data fusion results. | – Enabling medical experts to provide feedback on the accuracy and relevance of data fusion results to improve disease diagnosis and treatment.<br>– Enabling transportation experts to provide feedback on the accuracy and relevance of data fusion results to optimize transportation infrastructure. |
| Interactive data fusion | Developing methods to enable interactive data fusion, where users can interact with data fusion algorithms to explore and analyze data in real time. | – Enabling users to interact with data fusion algorithms to explore and analyze social media data in real time.<br>– Enabling users to interact with data fusion algorithms to explore and analyze financial data in real time. |

an inclination towards LLMs due to their remarkable capabilities, we strongly recommend giving consideration to the potential benefits that these methods can offer.

## CRediT authorship contribution statement

**Sahar Hassani:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Formal analysis, Validation, Resources, Visualization. **Ulrike Dackermann:** Writing – review & editing, Supervision. **Mohsen Mousavi:** Writing – review & editing. **Jianchun Li:** Writing – review & editing, Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

No data was used for the research described in the article.

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