applied sciences

Article

Review of Soft Computing Techniques in Monitoring Cardiovascular Disease in the Context of South Asian Countries

Gajendra Singh Thakur [1], Sunil Kumar Sahu [1], N. Kumar Swamy [1], Manish Gupta [2], Tony Jan [2] and Mukesh Prasad [3,*]

[1] School of Science, ISBM University, Nawapara (Kosmi) Block & Tehsil-Chhura, Gariyaband 493996, India
[2] Centre for Artificial Intelligence Research and Optimization (AIRO), Design and Creative Technology Vertical, Torrens University, Ultimo, NSW 2007, Australia
[3] Department of Computing Science, Faculty of Information Technology and Engineering (FEIT), University of Technology Sydney (UTS), Sydney, NSW 2007, Australia
* Correspondence: mukesh.prasad@uts.edu.au

Abstract: The term "soft computing" refers to a system that can work with varying degrees of uncertainty and approximations in real-life complex problems using various techniques such as Fuzzy Logic, Artificial Neural Networks (ANN), Machine Learning (ML), and Genetic Algorithms (GA). Owing to the low-cost and high-performance digital processors today, the use of soft computing techniques has become more prevalent. The main focus of this paper is to study the use of soft computing in the prediction and diagnosis of heart diseases, which are considered one of the major causes of fatalities in modern-day humans. The heart is a major human organ that can be affected by various conditions such as high blood pressure, diabetes, and heart failure. The main cause of heart failure is the narrowing of the blood vessels due to excess cholesterol deposits in the coronary arteries. The objective of this study is to review and compare the various soft computing techniques that are used for the prediction, diagnosis, failure, detection, identification, and classification of heart disease. In this paper, a comprehensive list of recent soft computing techniques in heart condition monitoring is reviewed and compared with an experiment with specific applications to developing countries including South Asian countries. The relevant experimental outcomes demonstrate the benefits of soft computing in medical services with a high accuracy of 99.4% from Fuzzy Logic and Convolutional Neural Networks, with comparable results from other competing state-of-the-art soft computing models.

Keywords: soft computing; cardiovascular diseases (CVDs); machine learning models

check for updates

Citation: Thakur, G.S.; Sahu, S.K.; Swamy, N.K.; Gupta, M.; Jan, T.; Prasad, M. Review of Soft Computing Techniques in Monitoring Cardiovascular Disease in the Context of South Asian Countries. *Appl. Sci.* **2023**, *13*, 9555. https://doi.org/10.3390/app13179555

Academic Editor: Andrea Prati

Received: 11 July 2023
Revised: 4 August 2023
Accepted: 22 August 2023
Published: 23 August 2023

1. Introduction

Because of the increasing quantity of data generated in the healthcare domain, it is important that the correct information is collected and used to improve the diagnosis of patients. Machine learning techniques are being studied to identify patterns in the data collected by healthcare facilities and to use them to improve the diagnosis of diseases. These techniques are also used in various medical services to enhance the efficiency of their operations. Data mining involves the extraction of valuable information from vast databases. It is performed using an interactive method that consists of various states, such as visualization, machine learning, statistical, and neural network learning. Because of the increasing popularity of data mining, these techniques have been refined to provide more robust and accurate solutions. The main challenge faced by data mining is the difficulty of handling complex and ambiguous situations. In terms of data mining, the use of soft computing has been widely promoted due to its ability to improve the accuracy rate and reduce time constraints. This data mining method has been used previously in healthcare. Heart disease is a condition that occurs when the heart cannot function properly. It usually manifests as a blocked artery supplying blood to the heart. Heart disease is one of the leading causes of death globally and can be triggered by various factors, such as age, gender, smoking, and alcohol consumption. Some of these include underemployment, stress, and anxiety. The prevalence of these diseases has increased in the population due to the busy lifestyles of people currently, and the level of consciousness of their health has become quite worrying [1].

Out of the 17.9 million deaths due to cardiovascular diseases (CVDs) in 2016, 85% were caused by heart attack and stroke. Almost all CVD deaths occur in low- and middle-income countries, where raised blood pressure is considered one of the most common risk factors. One-quarter of all deaths in India are caused by CVDs, and other causes are Ischemic heart disease and stroke [2]. It is very important that people regularly monitor their health and recover from any chronic diseases. In most cases, uncertainties and biases occur during the healthcare decision-making process. Therefore, the use of soft techniques has become crucial [2]. Automated and cost-effective soft computing solutions can democratize otherwise expensive medical services, therefore saving many lives in developing countries. This research contributes to understanding the insights and performance of soft computing automation in heart disease monitoring, with immense societal impacts.

2. Literature Review

In this section, we discuss 49 research papers published in Springer, IEEE, and other Q1/Q2 peer-reviewed journals from 2015 to 2021. The main keywords/filters used to search the targeted 58 papers were "Soft computing based methods for prediction of heart attack with accuracy more than 80%". This section is divided into four review subsections: prediction, diagnosis, failure of heart disease, and the last subsection considers soft computing techniques for the classification, identification, and detection of heart disease.

2.1. Review on Heart Disease Prediction by Using Soft Computing Techniques

Through machine learning techniques such as Adaboost, it is possible to identify patterns in data that can be used for clinical data analysis. Prakash et al. [3] performed a two-stage analysis to examine the attributes and classifications of patients with heart failure. The results of the study revealed that, although the system had only 13 attributes, it still retained plenty of information about the disease. The data collected by various classifiers were analyzed. Adaboost with a Decision Tree (DT) achieved the highest performance across all datasets. However, there were a few concerns with the data distribution.

Santhanam et al. [4] developed a system that can diagnose heart diseases using Fuzzy Logic and a Genetic Algorithm. A Genetic Algorithm was used to solve the feature selection problem. The data collected during the course of the study were then used to develop a fuzzy inference system. Their work used a Genetic Algorithm to select the relevant subset of rules for predicting heart disease in patients. Some of the key features that could be predicted using this algorithm included sex, serum cholesterol, exercise-induced angina, and depression [5,6]. This work was evaluated using various performance metrics, such as accuracy, sensitivity, and specificity, to evidence the efficiency of the system. The proposed system achieved an accuracy of 86% through a stratified k-fold technique that used the values for sensitivity and specificity. The proposed model, which was called Genetic Algorithm Fuzzy Logic, is commonly used in hospitals and medical centers. The various forms of data collected from a patient's medical history can be used to predict the risk of heart disease. To remove uncertainty from the data, a membership function was introduced that allowed users to customize the data collected.

Satapathy et al. [7] used a minimum-distance K-NN classifier and discovered that the Fuzzy K-NN classifier performed well compared to other parametric model-based classifiers. A similar system was developed by Paul et al. [8] that used a fuzzy rule base to predict heart diseases. It was able to achieve an accuracy of approximately 80%. The model was constructed using a modified differential evolution method, Analytic Hierarchy Process(AHP), and a Feedforward Neural Network (FNN). The model with the most important features was then chosen, and the attributes were then fed into the network.

Vivekanandan et al. [9] further optimized the model to predict heart disease using fuzzy AHP with an FNN. The proposed method was formulated to reduce computational time and improve accuracy. It was tested and achieved an accuracy of 84.16% [10]. Saini et al. [11] presented hybrid data-mining techniques in 2017. This study showed that these techniques can be used to extract valuable information from large amounts of data by taking advantage of the various attributes of the data. A back-propagation algorithm was proposed to predict the likelihood of a person developing heart disease. It used various medical terms such as blood pressure, cholesterol, and sex to identify potential risk patients [12]. The proposed heart disease risk prediction system consisted of two stages: the mechanized development of rules, and the building up of a fuzzy principle based on a genetic algorithm. The framework is then built based on weighted fuzzy standards. Subsequently, it can identify the most appropriate risk level for a given patient. The goal of this study was to help non-specialized doctors to make the right choice regarding the risk level of a patient with coronary illness [13].

Haq et al. [14] proposed a system for predicting heart disease using various techniques, such as Fuzzy Logic, Decision Trees, Support Vector Machines (SVM), Artificial Neural Networks, and Adaboost. The proposed system was evaluated using the Least Absolute Shrinkage and Selection Operator (LASSO), feature selection, and mRMR. The authors found that it performed well owing to a reduction in the set of features. In 2019, Amin et al. [15] developed a novel method for recognizing the relevant features of heart disease using data-mining techniques. They introduced various prediction schemes based on various features. This method was able to improve the accuracy of heart disease prediction. Ali et al. [16] proposed a x2-Deep Neural Network (DNN) model to predict heart disease. The authors noted that this could be affected by overfitting or underfitting. The authors compared their proposed model to existing models, such as ANN and DNN. They found that the prediction accuracy of their proposed model was 93.33%. Mohan et al. [17] proposed a method that combined the Hybrid Random Forest with a Linear Model (HRFLM) feature selection algorithm with a Random Forest model to predict heart diseases. The algorithm was optimized to detect features that are important for the prognosis of heart disease. The prediction accuracy of the model was 88.7%.

Al-Makhadmeh et al. [18] presented an example of an Internet of Things-based system that used deep neural networks to identify missing values. The data collected by the system were then analyzed, and features were extracted from the data. According to previous studies, heart disease is the primary cause of death worldwide. Being able to predict a patient's future health condition can help doctors to diagnose and treat the disease at an earlier stage. Being able to predict a patient's condition at an early stage can help prevent them from experiencing severe heart disease or its detrimental consequences. This paper aims to study various techniques that can be used to improve the accuracy of predicting a patient's heart disease. Wu et al. [19] conducted experiments to determine the best algorithm for predicting heart diseases. The authors then established an approach to tackle the issues caused by the predictive model. Through this method, the predictions were able to eliminate the issues caused by the overfitting and underfitting of the models, network configuration, and other inappropriate features from the data. Ali et al. [16] focused on four classifiers used to detect heart disease. Bashir et al. [20] revealed that Logistic Regression SVM achieved an accuracy of 84.85%. The hybrid system was then expanded to include 11 input variables. Tarawneh et al. [21] compared various classification techniques with the conventional approach. The authors aimed to develop an improved feature selection algorithm that can predict the mortality rate of patients with congestive heart failure. The algorithm was implemented using a Cleveland Case Study. The experimental results showed that the Hybrid K-Nearest Neighbor (HKNN) prediction model provided better results than the standard model.

Sowmiya et al. [22] further introduced ACO-HKNN with extended experiments. Machine learning technology has been widely used to predict various health conditions. This study aimed to develop a method that combines feature selection and dimensionality reduction to identify the various symptoms of heart disease. The data collected for this study were obtained from the UCI machine learning repository. It contained a large number of features and labels, which were verified using six machine-learning classifiers. The proposed method [22] identified various symptoms of heart disease such as high blood pressure, chest pain, and cholesterol. Gárate-Escamila et al. [23] also detected features related to ST depression, and the goal of this study was to develop a novel method to predict heart disease. It combined data collected by the Cleveland and Stalog databases. The resulting dataset contained over 500 instances of prediction and training for heart disease. Hassani et al. [24] presented a novel method that combined the capabilities of a neural network and Decision Tree to test the effectiveness of its prediction method for classifying heart disease. The results of the study revealed that the system was able to improve its accuracy and performance compared with other methods. During the past few decades, various countries have seen an alarming rise in the number of deaths due to various types of heart disease. The reason for this is the increasing number of people with these diseases. Owing to the large amount of data collected and analyzed, various techniques are used to analyze it. These techniques can aid in the diagnosis of various heart diseases. Patel et al. [25] introduced various supervised learning algorithms that were commonly used in data analysis. Some of these included the Random Forest, Decision Tree, and ensemble models [25].

2.2. Review on Diagnosis of Heart Disease by Using Soft Computing Techniques

Misdiagnosis and ignorance are factors that contribute to the increasing death rate due to heart disease. Heart disease is a disorder that affects the circulatory system. Olaniyi et al. [26] proposed a system that can accurately diagnose heart diseases. Their work prevented major errors that can occur when patients are referred to a specialist. The proposed system analyzed the data collected by UCI Machine Learning to diagnose patients. The same study was performed by asking the patients if they had heart disease. The recognition rates of various models were compared to determine the best diagnosis model. The results indicated that the Support Vector Machine was the most accurate network for detecting heart diseases in their studies.

Akinyokun et al. [27] used Fuzzy Logic to diagnose heart diseases. It can provide accurate and comprehensive solutions by considering all the factors that affect the diagnosis. The concept of the system involved a three-tier architecture composed of a front-end, middle-end, and back-end. The front-end engine served as the platform, whereas the middle-end provided the application engine. The features and functionalities of the system were designed to provide a personalized and secure environment for users. Its privacy and security features were implemented to prevent unauthorized users from accessing the system. Feshki et al. [28] developed a fatal heart disease diagnosis system based on a radial basis function neural network (RBFNN). Their model used data collected by the Beth Hospital and Massachusetts Institute of Technology. Their system could classify the features of heart disease based on heart-rate intervals with an accuracy of 96.3%. Baihaqi et al. [29] developed a fuzzy expert system that used 13 input variables, including angiography status and a number of output variables. Their algorithm was optimized using the imperialist competitive algorithm (ICA). Uyar et al. [30] applied a recurrent fuzzy network Genetic Algorithm to analyze the data collected for heart disease diagnosis in their study. The authors trained the algorithm on the data collected by applying genetic operators. The recurrent network could classify the data based on the patient's conditions. Nalluri et al. [31] proposed a hybrid metaheuristic algorithm that combined the prediction of heart disease with support vector machines. The results of their study showed that the hybrid algorithm could predict the outcomes of various datasets well.

Nazari et al. [32] considered various factors that affected the development and probability of heart disease and then recommended further medical testing. Owing to the complexity of disease data, decision support systems are primarily used for the automatic diagnosis of human diseases. The performance of these systems depends on the selection of the most appropriate features. Shah et al. [33] presented a method that used the results of medical tests to extract and analyze a reduced-dimensional feature subset of a disease. This method was performed through parallel analysis to select the features that were most suitable for the diseases. The feature subsets with a reduced dimension were then classified into two categories: heart and normal subjects. The proposed method was evaluated using three datasets—the European Union's (EU) database, the Cleveland Clinic database, and the Hungarian Health Study database—with a comprehensive comparison with the previous studies [33]. The study of Chui et al. [34] analyzed various smart healthcare systems, including information communication technology and the Internet of Things, for their effectiveness in diagnosing diseases. A combination of these approaches can improve the diagnostic process by identifying diseases that are already present. However, the necessary data analysis skills to properly interpret the results were lacking. Kasbe et al. [35] designed and implemented a fuzzy expert system that used 10 input variables and was characterized by rules linked to attributes. The algorithm achieved 93.33% accuracy by defuzzifying multiple datasets. This was computed using the Center-of-Gravity approach. Alqudah et al. [36] proposed a Fuzzy Logic controller to predict the risk of coronary heart disease based on the input variables. A rule-based system was also used to represent the inputs.

Pawlovsky et al. [37] introduced two ensembles based on the kNN methods, and two implementations with weights were demonstrated. Their results showed that the weighted three-distance ensemble, which used the Manhattan and Euclidean distances, can yield an average accuracy of almost 85% when used with the Cleveland data set. The accuracy of the algorithm was higher by 10% when compared to the raw data. The same method was tested using only 10 trials. Evaluations of 10-fold cross-validation or 10-trial evaluation usually show higher accuracy than those of 100 trials. Madaan et al. [38] proposed a Fuzzy Inference System in 2018 to solve the problem of diagnosis by taking into account six input parameters. Their work obtained an 82.65% accuracy in diagnosis. In 2018, Iancu et al. [39] presented a meditative Fuzzy Logic system. This system considered 11 input variables: cholesterol (CHL), blood pressure (BP), maximum heart rate (MHR), resting electrocardiography (RECG), old peak (OP), and gender ratio (GR). This system was tested using a database from three hospitals. Defuzzification was performed using a simple algorithm. Kahtan et al. [40] proposed an FL system with three inputs: BP, age group (AG), and CHL. The system was fuzzified using a trapezoidal membership function. Nourmohammadi-Khiarak et al. [41] presented a hybrid algorithm to classify heart diseases. The authors used a metaheuristic technique to improve feature selection, and the proposed algorithm was tested on multiple datasets. The accuracy of their method was 94.03% [41]. The challenges of analyzing data related to heart disease include the selection of features, the number of samples, and the imbalance of samples. Jain et al. [42] proposed a competitive algorithm to improve the selection process. The proposed algorithm provided a better response to the feature selection of genetic samples. It could also classify data according to their complexity. The medicinal services industry is flourishing worldwide. As the number of people suffering from various illnesses increases, information about patients will be extended. Muhammad et al. [43] developed a fuzzy expert system to help identify patients with coronary artery heart disease. Bohacik et al. [44] focused on the development of a fuzzy-based expert system for the diagnosis of coronary artery disease (CAD). It was created using an improved data mining algorithm with an overall accuracy of 94.55% and a sensitivity of 95.35%.

2.3. Review on Failure of Heart Disease by Using Soft Computing Techniques

Samuel et al. [45] developed an algorithm using data from the same patients from the University of Hull and York medical school, England. Their algorithm was able to detect the presence of heart disease in 2032 patients with an accuracy of 64.41% and specificity of 63.27%. Jin et al. [46] analyzed the contributions of 13 commonly used attributes of heart disease. The weighted global weights for these attributes were computed using a

Fuzzy Analytic Hierarchy process. The global weights were then computed and trained on an ANN classifier to predict the risk of heart disease in the patients. The system was evaluated using a clinical dataset comprising 297 patients. The proposed method was able to achieve an accuracy of 91.10%, which is 4.40% higher than that of the conventional ANN method. It also exhibited better performance than previous methods [46]. In 2018, a number of research teams presented a framework for predicting heart malfunctions. Driscoll et al. [47] used word vectors and one-hot encoding to model the various symptoms of heart disease. The results of their experiments showed that the framework could predict the likelihood of heart failure. Valenza et al. [48] introduced a scheme to address the limitations of risk prediction models that only accounted for certain clinical parameters. The multivariable risk factor approach was used to predict the likelihood of hospitalization or death in the study population. A risk score was then extracted to evaluate various risk categories. The scientists involved in the study noted that the data collected during the continuous-time periods of a heartbeat can provide an estimate of multifractal autonomic dynamics [49,50]. The framework was then merged with the data collected during the heartbeat. Wang et al. [51] then used a statistical framework to predict the time until the next heartbeat occurred. The authors [51] used a statistical framework to predict the mortality rate of patients receiving heart failure treatment. The prediction tool helped prevent overtreatment and undertreatment in patients with low mortality. The authors then focused on three key factors to predict the mortality rate of patients: hospital admission, 1-year mortality prediction, and 30-day mortality prediction. In 2019, Wang et al. [52] further proposed a multitask deep and wide neural network (MT-DWNN) to predict serious problems during hospitalization. The proposed network could identify the most critical factors that could affect a person's condition. The results of the study showed that the network was able to improve the forecasting performance of HF patients compared to traditional methods. In the same year, Samuel et al. [53] proposed a method that combines multilayer networks and a hierarchical component-based learning model to predict heart disease. This method was able to learn the interrelations among various risk factors. The results of the study revealed that the network could achieve higher predictions than the standard method.

2.4. Review on Classification, Identification, and Detection of Heart Disease by Using Soft Computing Techniques

In 2015, Yang et al. [54] developed a hybrid model for the HF diagnosis of heart failure using the machine learning for language toolkit (MALLET). The system used seven main risk factors for heart stroke to identify the risk factors. In 2016, Duisenbayeva et al. [55] demonstrated a more adaptable fuzzy inference system that aids doctors in making informed decisions regarding patients with coronary artery disease (CAD). CAD is one of the main causes of death worldwide. It is considered a major illness in old and middle age groups. Owing to the nature of data mining techniques used in the development of such systems, it has become increasingly challenging for experts to provide an accurate diagnosis of CAD. Arabasadi et al. [56] developed a hybrid method that combined the findings of various studies and incorporated a Genetic Algorithm. Through this study, the authors achieved an overall accuracy of 94.55% and a sensitivity of 95.35%. Yazid et al. [57] proposed a neural network parameter-tuning framework for the classification of heart diseases. It achieved a high classification accuracy with respect to the Cleveland and Statlog datasets. Makhlouf et al. [58] proposed a framework that achieved similar classification accuracy to that of [57].

Vijayashree et al. [59] proposed a system consisting of three services: an emergency service, a fall detection service, and a heart disorder detection service. The system used a combination of sensors. The system sent detailed information regarding a person to a doctor. It used a combination of sensors, timed Petri nets, and stochastic Petri nets. The authors conducted tests on 10 subjects to reveal that the system can detect falls with a high degree of accuracy and specificity. These results also validated the detection of tachycardia. Machine learning is an effective support system for health diagnoses that can analyze large volumes of data. However, this consumes a large amount of resources and time to perform tasks. Owing to the complexity of data, it is necessary to use an algorithm that can identify the most important features that contribute to the success of machine learning. Particle Swarm Optimization (PSO) is a good choice for this purpose. The current PSO algorithm cannot update the position and velocity of the particles because of its dependence on the optimal weight. Navaneeth et al. [60] proposed a novel function that can identify optimal weights. The goal of this study was to improve accuracy and minimize the number of attributes. It was compared with various feature selection algorithms that were used to determine the optimal weights. The authors of [60] focused on the use of a swarm Convolutional Neural Network to diagnose heart diseases. The procedure was performed by analyzing the data collected from the kidneys of the test subjects. The data were analyzed using a swarm intelligence training system before it was classified into various features. The system then diagnosed heart disease with 98.25% accuracy. A fuzzy-based framework was presented in 2019 by Padmavathi Kora et al. [61]. This system was developed to detect valvular heart disease by considering seven clinical input variables. It was implemented using a rule-set system and the Mamdani inference framework. The data collected for this study were used as the source of the ROC curve. Alkhodari et al. [62] developed a model by combining the data collected by the CNN and the BiLSTM networks. It was able to identify 99.30% of all valvular heart diseases. Das et al. [63] utilized time series analysis reinforced with a rough set technique in predicting heart disease with validated and comparable success with further improvements in [64].

3. Comparative Analysis on Accuracies/Techniques

This section is divided into a concise description of the experiments, the interpretation of the experimental outcomes, and the conclusions. In the following, Table 1 present the authors, year, methodologies, accuracy, sensitivity, and specificity where the information is available.

The review of soft computing in the identification, classification, and detection of heart disease in Table 1 showed that Fuzzy Logic and Convolutional Neural Networks achieved the highest accuracy of 99.30%.

Table 1. Methodology and accuracy of soft computing techniques for prediction of heart disease.

No.	Authors	Year	Methodology	Accuracy	Sensitivity	Specificity
01	Prakash et al.	2017	PNN, GRNN	98%	NA	NA
02	Santhanametal et al.	2015	HybridGA-Fuzzy,ANN	86%	0.80	0.90
03	Satapathy et al.	2014	FuzzyK-NN	91%	NA	NA
04	Pauletal et al.	2016	GFDSS	80%	0.60	0.95
05	Vivekanandan et al.	2017	Fuzzy Logic, feedforward neural network	83%	0.84	0.89
06	Pahwa et al.	2017	Gain-Ratio algorithm, SVM-REF	84.16%	0.85	0.82
07	Sainietal et al.	2017	HCWV	82.54%	NA	NA
08	Nalluri et al.	2017	XGBoost and logistic regressor	85.86%	0.86	0.69
09	Sharmaetal et al.	2017	Fuzzy Logic, GA	88.11%	0.92	0.27
10	Amin Ul Haq et al.	2018	Hybrid intelligent system-MLR	88%	0.75	0.96
11	Aminetal et al.	2018	KNN, SVM, Naïve Bayes, LR, hybrid Naïve Bayes-LR, Vote	87.41%	0.79	NA

Table 1. *Cont.*

No.	Authors	Year	Methodology	Accuracy	Sensitivity	Specificity
12	Alietal et al.	2019	X2-DNN	93.33%	0.85	100
13	Mohanetal et al.	2019	HRFLM	88.7%	0.92	0.82
14	Makhadmeh et al.	2019	HOBDBNN	99.03%	0.9983	0.9904
15	Wu et al.	2019	DT, MLP, LR, SVM, NB	84%	NA	NA
16	Bashiretal et al.	2019	SVM, DT, Random Forest, NB	84.85%	NA	NA
17	Tarawneh et al.	2019	ANN, SVM, GA, DT, KNN	89%	0.83	0.84
18	Sowmiyaetal et al.	2020	HKNN, ant colony optimization	99.2%	0.97	0.98
19	Garate-Escamila et al.	2020	CHI-PCA and RF	99.4%	1.00	0.98
20	Alietal et al.	2020	NNDT	99.2%	0.98	0.99
21	Patel et al.	2021	ANN, SVM and DT	92.56%	0.86	1.00
22	Olaniyietal et al.	2015	Feed-forward multi-layer perception and SVM	87.5%	0.84	0.89
23	Feshki et al.	2016	PSO and Feedforward Backpropagation	91.94%	0.91	0.93
24	Baihaqietal et al.	2016	Fuzzy Logic	81.82%	0.78	0.84
25	Uyaretal et al.	2017	GA-RFNN	97.78%	0.97	0.95
26	Nallurietal et al.	2017	SVM and MLP	97%	97.4	98.7
27	Shahet et al.	2017	Probabilistic principal component analysis	91.30%	1.00	0.50
28	Kasbeand et al.	2017	Fuzzy Logic	93.33%	NA	NA
29	Pawlovskyetal et al.	2018	KNN	85%	NA	NA
30	Madaanetal et al.	2018	Fuzzy Logic	85%	NA	NA
32	Kahtan et al.	2018	Fuzzy Logic	98%	NA	NA
33	Nourmohammadi-Khiarak et al.	2019	Imperialist Competitive Algorithm (ICA) and K-nearest neighbor	88%	0.94	0.83
34	Muhammad et al.	2021	Fuzzy Logic and Random Forest	94.55%	0.95	0.95
35	Bohaciketal et al.	2015	Fuzzy logic	94.55%	0.63	0.65
36	Atal. et al.	2016	Fuzzy analytic hierarchy process	91.10%	1.00	0.84
37	Jin et al.	2017	ANN and LSTM	NA	0.26	0.26
38	Valenzaetal et al.	2018	Multi fractal point process	79%	0.90	0.67
39	Wangetal et al.	2018	OR, DRM	84.84%	NA	NA
40	Wangetal et al.	2019	MT-DWNN	93%	0.93	0.90
41	Williams et al.	2019	HNCL, AMLN	97.80%	0.95	1.00
42	Yang et al.	2015	MLM	91.5%	0.88	0.94
43	Arabasadi et al.	2017	NN-GA	93.85%	0.97	0.92
44	Yazid et al.	2018	ANN 90.9%	NA	NA	
45	Makhlout et al.	2018	Machine learning	87%	0.82	0.92
46	Vijayashree et al.	2018	PSO-SVM	84.36%	NA	NA
47	Baskar et al.	2019	PSO, 1-DCNN-SVM	98.25%	0.98	0.98
48	Koraet al.	2019	Fuzzy logic	99.3%	98.3	98.2
49	Alkhodari et al.	2021	CNN, BiLSTM	99.30%	0.99	0.99

4. Case Study of Cardio-Vascular Disease Using Fuzzy Logic

This section demonstrates a typical case study of predicting the risk of cardiovascular disease with various learning algorithms including Fuzzy Logic [65–69]. This real data-based experiment was performed to consolidate and verify Fuzzy Logic and CNN and various other popular soft computing solutions in heart disease monitoring for patients in a Southern Asian country.

4.1. Intelligent System and Experimental Framework

This subsection introduces a proposed architecture of the Smart Early Heart Attack Prediction (SEHAP) Model. This model was developed using the Internet of Things (IoT) to track the well-being of heart patients. In this model, we combined biosensors that were implemented with a Raspberry Pi interface via wires and Wi-Fi. Figure 1 presents a high-level overview of the proposed model including the stages of data gathering, data storing, data analysis and predictive analysis, and data visualization as the five main components of the proposed model architecture. An IoT server received data collected by biosensors from the patient dummy, as depicted in Figure 1.

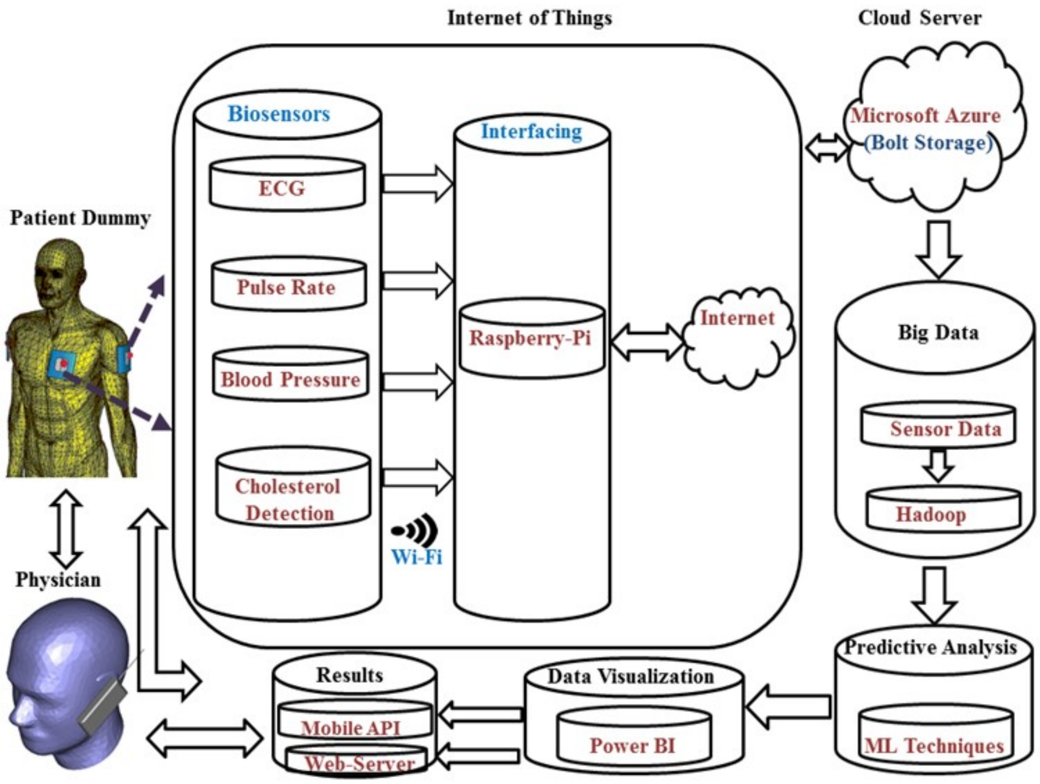

Figure 1. Graphical representation of the expert system.

The sensor data were gathered and stored on a cloud server. In this case, we used a private cloud with virtual machines in a Hadoop cluster. Data analysis could be carried out using either a statistical method or a more sophisticated machine learning algorithm as discussed in this paper. We wanted to be able to run cutting-edge machine learning algorithms on the collected data to identify potential heart attacks in the future. Finally, it was possible to employ data visualization techniques that would result in a mobile application and a web server. By doing this, not only could valuable rescue time be preserved, but there could also be a chance to detect heart attacks early on. Therefore, our intelligent system can save the lives of many people with chronic diseases, especially those with heart diseases. In the following Section 4.2, further heart disease diagnosis is explained.

4.2. Heart Disease Diagnosis

In this case study, there were eight inputs and one output.

- **Cholesterol.** This input variable has four linguistic variables: normal, medium, high, and very high. The normal and very high values were represented in trapezoidal membership functions, while the others (medium and high) were represented in triangular membership functions. The range for cholesterol was taken as [0–500], as represented in Figure 2.

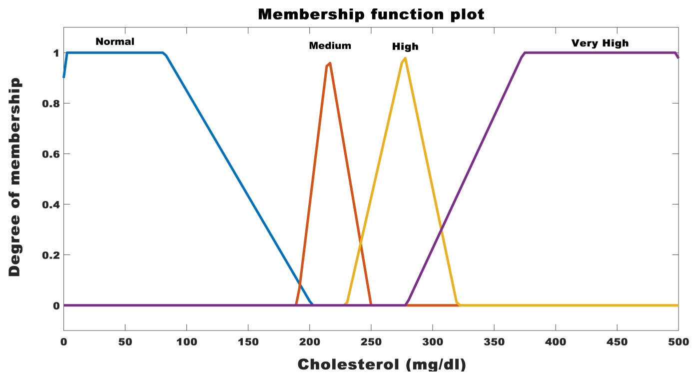

Figure 2. Membership function of cholesterol.

- **Body mass index (BMI).** This input variable had four membership functions, which were "underweight range (UR)", "healthy range (HR)", "overweight range (OWR)", and "obese range (OR)", shown in Figure 3.

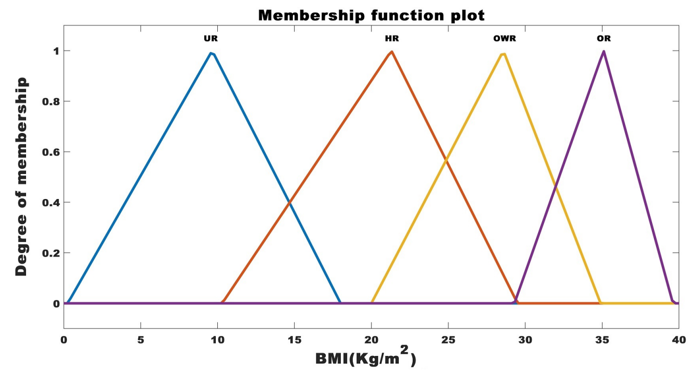

Figure 3. Membership function of body mass index.

- **Age.** The input linguistic variables were divided into four parts, 'young', 'medium,' 'old', and 'very old', as depicted in Figure 4.

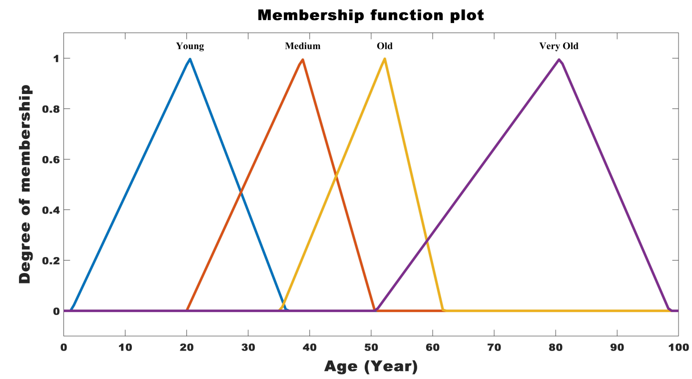

Figure 4. Membership function of age.

- **Blood bressure (BP).** Blood pressure was divided into three categories: normal, medium, and high. The range for blood pressure was [0 200]. The normal and high linguistic variables used trapezoidal membership functions, as shown in Figure 5.

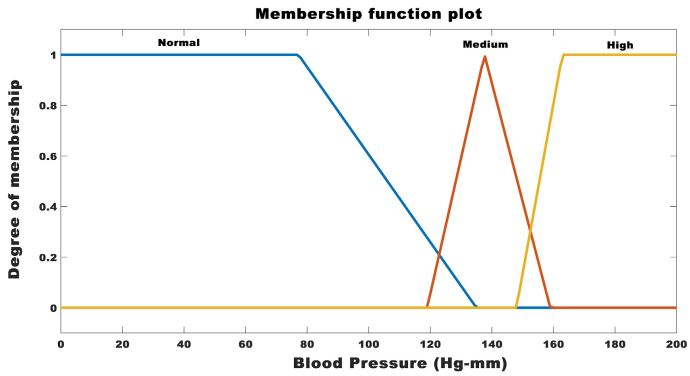

Figure 5. Membership function for blood pressure.

- **Gender.** This input variable supports two types: male and female. Both linguistic variables are shown as the triangular membership function in Figure 6.

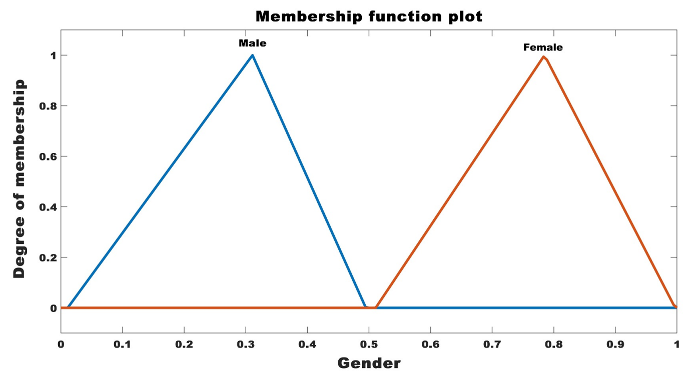

Figure 6. Membership function of gender.

- **Diabetes.** This input variable also shows the two types of diabetes and normal, as shown in Figure 7.

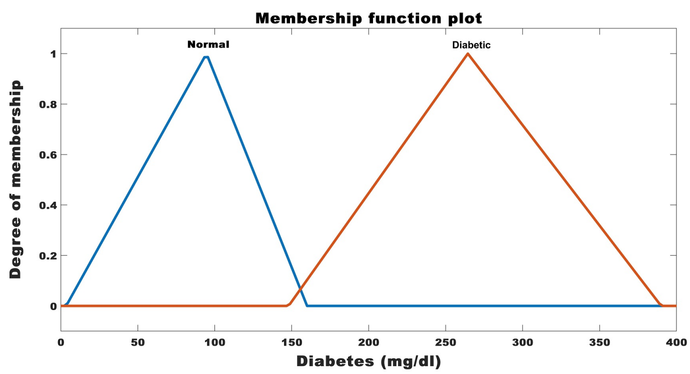

Figure 7. Membership function of diabetes.

- **Smoker.** The input variable is "smoker", which contains two parts: the first part is nonsmoker and the second part is smoker, as shown in Figure 8.

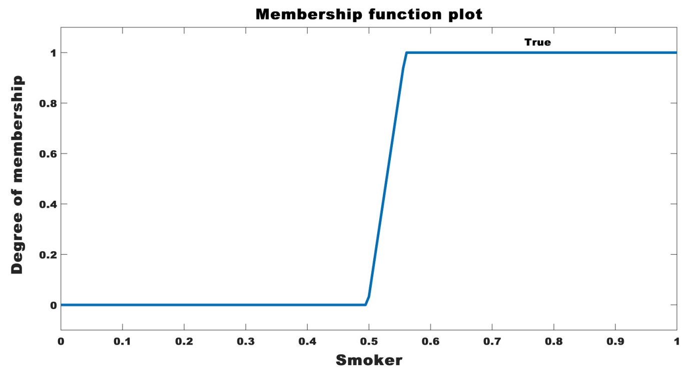

Figure 8. Membership function for smoker.

- **Physical activity.** This input field had two values: 0 (false) and 1 (true). If the patient exercises regularly, then value = 1; otherwise, value = 0, as shown in Figure 9.

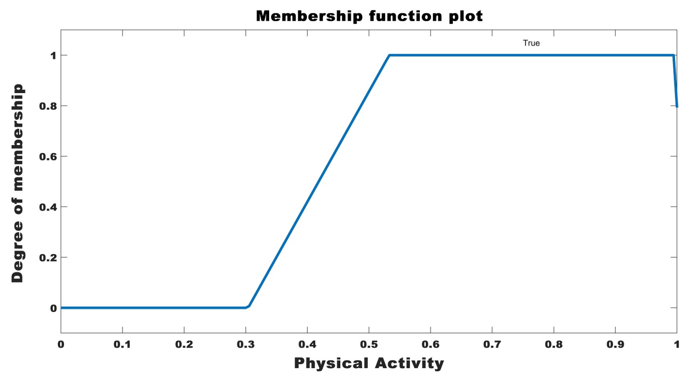

Figure 9. Membership function for physical activity.

- **Output variable**. To predict the risk level of cardiovascular disease, the output variables were of three types, healthy, early stage, and advanced stage, as shown in Figure 10.

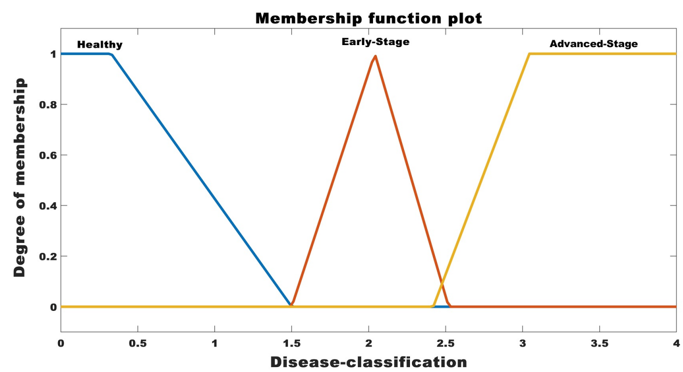

Figure 10. Output variable disease classification.

- **Fuzzy rule-based**. The next step was to enter the rules into the system. The rule was then inserted using a rule-based system. This is the main component of a fuzzy interface system. The output of the expert system is dependent on what is inserted into it, and 40 rules were inserted for the risk level of cardiovascular disease [70–73]. The rules are as follows:
    - If (Age is Y) and (BMI is UR) and (Cholesterol is N) and (Blood Pressure is Normal) and (Smoker is True) and (Diabetes is Normal) and (Physical Activity is True) and (Gender is M), then (Disease classification is Healthy) (1)

- If (Age is Medium) and (BMI is UR) and (Cholesterol is Normal) and (Blood Pressure is Normal) and (Smoker is True) and (Diabetes is Normal) and (Physical Activity is True) and (Gender is Male), then (Disease classification is Healthy) (1).
- If (Age is Young) and (BMI is HR) and (Cholesterol is Medium) and (Blood_Pressure is Medium) and (Diabetes is Normal) and (Physical Activity is True) and (Gender is Male), then (Disease classification is Healthy) (1)
- If (Age is Medium) and (BMI is HR) and (Cholesterol is High) and (Blood Pressure is High) and (Smoker is True) and (Diabetes is Diabetic) and (Gender is Male), then (Disease classification is Early Stage) (1)
- If (Age is Very Old) and (BMI is OR) and (Cholesterol is Very High) and (Blood_Pressure is High) and (Diabetes is Normal) and (Physical Activity is True) and (Gender is Male), then (Disease classification is Advanced Stage) (1)

4.3. Experimental Outcomes

Figure 11 demonstrates the rule editor in classification. The rule editor can be used to create rule statements based on the details of the output and input variables defined in the FIS Editor. It can also automatically select one item from each box of the input variable and one item from the output box of the connection item. The rule viewer can help the user to analyze the entire fuzzy analysis process by allowing them to look at the various membership functions' shapes, as shown in Figure 11.

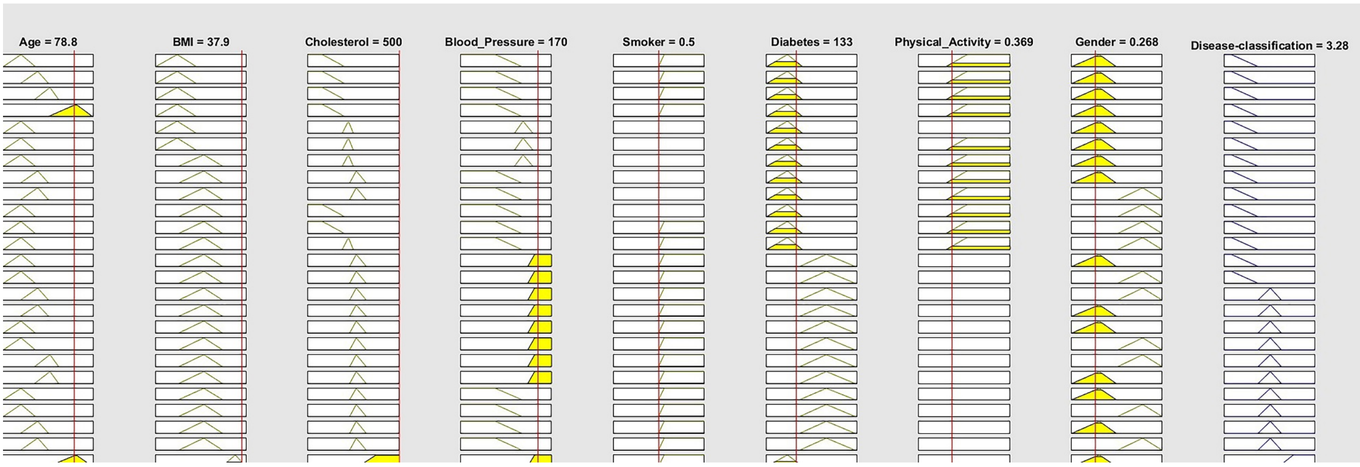

Figure 11. Example graphical representation of the rule editor in expert systems.

Table 2 shows the sample data collected from District Hospital Gariyaband, Chhattisgarh of 29 individuals, with input parameters including their age, BMI, cholesterol level, blood pressure, smoker, diabetes level, physical activity level, gender, and output parameter used for cardiovascular disease classification. To remedy the small data sample size, this research applied data augmentation techniques such as the Synthetic Minority Oversampling Technique (SMOTE) [74,75]. SMOTE is specifically designed to tackle imbalanced datasets by generating synthetic samples for the minority class.

Table 3 shows the detection performance of the popular soft computing models (which were top performers in the review). We implemented a number of popular classifiers on the cardiovascular data after applying data augmentation to mitigate the challenges of data imbalance and scarcity. In our experiments, the attention-based CNN outperformed other implemented classifiers. In the evaluation metric, it achieved a good level of accuracy, i.e., 99.53%, with a sensitivity of 0.99 and a specificity of 0.99. The experimental outcomes conformed to the survey review outcomes. The cardiovascular disease classification was based on the following criteria. Early stage: Individuals with one or more risk factors for cardiovascular disease, such as high blood pressure, high cholesterol, or smoking. Healthy: Individuals with no risk factors for cardiovascular disease. The cardiovascular disease classification was not a diagnosis; it was simply a way to identify individuals who may be at an increased risk for developing cardiovascular disease. Individuals who are classified as early stage should talk to their doctor about ways to reduce their risk of developing cardiovascular disease.

Table 2. Case example data with classification results.

Sample No.	Age (Years)	BMI (Kg/m^2)	Cholesterol (mg/dL)	Blood Pressure (Hg-mm)	Smoker (1/0)	Diabetes (mg/dL)	Physical Activity (1/0)	Gender (M/F)	Cardio-Vascular Disease Classification
1	35	20.8	169	138	1	135	1	F	Early stage
2	33	22.8	165	105	0	106	1	M	Early stage
3	65	24.2	195	152	0	154	0	M	Early stage
4	65	20.3	200	100	0	136	0	F	Early stage
5	27	20.7	170	119	0	132	1	F	Healthy
6	72	24.2	205	127	0	116	0	M	Early stage
7	50	23.4	195	146	0	126	1	M	Early stage
8	43	19.8	190	126	0	105	1	F	Healthy
9	33	23.4	203	137	0	103	1	M	Healthy
10	31	23.9	205	114	0	128	1	M	Healthy
11	45	25.7	220	135	0	86	1	M	Early stage
12	44	20.8	170	112	0	101	1	F	Healthy
13	29	20.7	145	116	0	117	1	F	Healthy
14	30	26.1	240	122	0	105	1	M	Early stage
15	55	26	245	158	0	123	0	M	Early stage
16	55	26.1	234	129	0	109	0	M	Early stage
17	38	24.8	215	129	0	333	1	M	Early stage
18	40	24.2	212	122	1	129	1	M	Healthy
19	36	24.5	208	113	0	128	1	M	Healthy
20	59	22.3	225	111	0	93	0	M	Healthy
21	27	22	170	85	0	153	1	F	Healthy
22	31	22	175	117	0	216	1	F	Healthy
23	26	22.7	172	136	0	150	1	F	Healthy
24	27	26.2	234	102	0	259	1	F	Early stage
25	53	24.2	215	127	0	159	0	M	Early stage
26	47	22.8	201	134	0	101	1	F	Healthy
27	26	20.7	165	113	0	128	1	F	Healthy
28	18	19.5	154	112	0	249	1	F	Healthy
29	24	20	155	112	0	124	1	M	Healthy

Table 3. Evaluation metrics on experimental data with respect to various popular classifiers.

Classifier	Accuracy	Sensitivity	Specificity
Gradient Boosting	98.61%	0.89	0.90
SVM	98.93%	0.90	0.91
Fuzzy Logic	99.15%	0.91	0.92
Attention-based CNN	99.53%	0.99	0.99

5. Conclusions

In this paper, we reviewed diverse research work into heart disease monitoring using soft computing techniques. This paper presented a detailed study and investigation of various articles published in numerous prestigious journals on the subject in recent years. The main result is that Fuzzy Logic and hybrid CNN achieved the highest accuracy, and other soft computing techniques using Genetic Fuzzy Logic, Fuzzy Neural, Adaptive Neuro-Fuzzy, Genetic Neuro-Fuzzy, and PSO with FL also performed well because FL has sufficient adaptability to diagnose heart disease. In terms of accuracy, Fuzzy Logic provided better accuracy than other methods, while Convolutional Neural Networks [76] provided competitive accuracy. This study provided an ample comprehensive study of soft computing techniques in diagnosing cardiovascular disease with an experiment to validate the review.

Author Contributions: Conceptualization, N.K.S. and S.K.S.; methodology, G.S.T.; software, S.K.S.; validation, S.K.S., G.S.T. and N.K.S.; formal analysis, S.K.S.; investigation, S.K.S.; resources, S.K.S. and M.G.; data curation, S.K.S.; writing—original draft preparation, S.K.S.; writing—review and editing, T.J.; visualization, S.K.S. and M.G.; supervision, N.K.S., T.J. and M.P.; project administration, N.K.S. and M.G.; funding acquisition, T.J. and M.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: First and second authors would like to thank Barada Prasad Bhol, Registrar, ISBM University, Nawapara (Kosmi), Gariyaband, C.G., India for valuable guidance.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BiLSTM	Bidirectional long short-term memory
CNN	Convolutional Neural Network
ROC curve	Receiver operating characteristic curve

References

1. Hu, F.; Qiu, L.; Xiang, Y.; Wei, S.; Sun, H.; Hu, H.; Weng, X.; Mao, L.; Zeng, M. Spatial network and driving factors of low-carbon patent applications in China from a public health perspective. *Front. Public Health* **2023**, *11*, 1121860. [CrossRef] [PubMed]
2. Ghosh, G.; Roy, S.; Merdji, A. A proposed health monitoring system using fuzzy inference system. *Proc. Inst. Mech. Eng. Part H J. Eng. Med.* **2020**, *234*, 562–569. [CrossRef] [PubMed]
3. Ajay Prakash, B.; Ashoka, D.; Manjunath Aradya, V. Exploration of Machine Learning Techniques for Defect Classification. In *Proceedings of the Computing and Network Sustainability: Proceedings of IRSCNS 2016*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 145–153. [CrossRef]
4. Santhanam, T.; Ephzibah, E. Heart disease prediction using hybrid genetic fuzzy model. *Indian J. Sci. Technol.* **2015**, *8*, 797. [CrossRef]
5. Wang, H.; Wang, K.; Xue, Q.; Peng, M.; Yin, L.; Gu, X.; Leng, H.; Lu, J.; Liu, H.; Wang, D.; et al. Transcranial alternating current stimulation for treating depression: A randomized controlled trial. *Brain* **2022**, *145*, 83–91. [CrossRef] [PubMed]
6. Li, C.; Lin, L.; Zhang, L.; Xu, R.; Chen, X.; Ji, J.; Li, Y. Long noncoding RNA p21 enhances autophagy to alleviate endothelial progenitor cells damage and promote endothelial repair in hypertension through SESN2/AMPK/TSC2 pathway. *Pharmacol. Res.* **2021**, *173*, 105920. [CrossRef] [PubMed]
7. Satapathy, S.C.; Govardhan, A.; Raju, K.S.; Mandal, J. *Emerging ICT for Bridging the Future-Proceedings of the 49th Annual Convention of the Computer Society of India (CSI) Volume 1*; Springer: Berlin/Heidelberg, Germany, 2014; Volume 337.
8. Paul, A.K.; Shill, P.C.; Rabin, M.R.I.; Akhand, M. Genetic algorithm based fuzzy decision support system for the diagnosis of heart disease. In Proceedings of the 2016 5th International Conference on Informatics, Electronics and Vision (ICIEV), Dhaka, Bangladesh, 13–14 May 2016; pp. 145–150. [CrossRef]
9. Vivekanandan, T.; Iyengar, N.C.S.N. Optimal feature selection using a modified differential evolution algorithm and its effectiveness for prediction of heart disease. *Comput. Biol. Med.* **2017**, *90*, 125–136. [CrossRef] [PubMed]
10. Pahwa, K.; Kumar, R. Prediction of heart disease using hybrid technique for selecting features. In Proceedings of the 2017 4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON), Mathura, India, 26–28 October 2017; pp. 500–504. [CrossRef]
11. Saini, M.; Baliyan, N.; Bassi, V. Prediction of heart disease severity with hybrid data mining. In Proceedings of the 2017 2nd International Conference on Telecommunication and Networks (TEL-NET), Noida, India, 10–11 August 2017; pp. 1–6. [CrossRef]
12. Nalluri, S.; Vijaya Saraswathi, R.; Ramasubbareddy, S.; Govinda, K.; Swetha, E. Chronic heart disease prediction using data mining techniques. In *Proceedings of the Data Engineering and Communication Technology: Proceedings of 3rd ICDECT-2K19*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 903–912. [CrossRef]
13. Sharma, P.; Saxena, K. Application of fuzzy logic and genetic algorithm in heart disease risk level prediction. *Int. J. Syst. Assur. Eng. Manag.* **2017**, *8*, 1109–1125. [CrossRef]
14. Haq, A.U.; Li, J.P.; Memon, M.H.; Nazir, S.; Sun, R. A hybrid intelligent system framework for the prediction of heart disease using machine learning algorithms. *Mob. Inf. Syst.* **2018**, *2018*, 3860146. [CrossRef]

15. Amin, M.S.; Chiam, Y.K.; Varathan, K.D. Identification of significant features and data mining techniques in predicting heart disease. *Telemat. Inform.* **2019**, *36*, 82–93. [CrossRef]
16. Ali, L.; Rahman, A.; Khan, A.; Zhou, M.; Javeed, A.; Khan, J.A. An Automated Diagnostic System for Heart Disease Prediction Based on $X2$ Statistical Model and Optimally Configured Deep Neural Network. *IEEE Access* **2019**, *7*, 34938–34945. [CrossRef]
17. Mohan, S.; Thirumalai, C.; Srivastava, G. Effective heart disease prediction using hybrid machine learning techniques. *IEEE Access* **2019**, *7*, 81542–81554. [CrossRef]
18. Al-Makhadmeh, Z.; Tolba, A. Utilizing IoT wearable medical device for heart disease prediction using higher order Boltzmann model: A classification approach. *Measurement* **2019**, *147*, 106815. [CrossRef]
19. Rairikar, A.; Kulkarni, V.; Sabale, V.; Kale, H.; Lamgunde, A. Heart disease prediction using data mining techniques. In Proceedings of the 2017 International Conference on Intelligent Computing and Control (I2C2), Liverpool, UK, 7–10 August 2017; pp. 1–8. [CrossRef]
20. Bashir, S.; Khan, Z.S.; Khan, F.H.; Anjum, A.; Bashir, K. Improving heart disease prediction using feature selection approaches. In Proceedings of the 2019 16th International Bhurban Conference on Applied Sciences and Technology (IBCAST), Islamabad, Pakistan, 8–12 January 2019; pp. 619–623. [CrossRef]
21. Tarawneh, M.; Embarak, O. Hybrid approach for heart disease prediction using data mining techniques. In *Proceedings of the Advances in Internet, Data and Web Technologies: The 7th International Conference on Emerging Internet, Data and Web Technologies (EIDWT-2019)*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 447–454.
22. Sowmiya, C.; Sumitra, P. A hybrid approach for mortality prediction for heart patients using ACO-HKNN. *J. Ambient. Intell. Humaniz. Comput.* **2021**, *12*, 5405–5412. [CrossRef]
23. Gárate-Escamila, A.K.; El Hassani, A.H.; Andrès, E. Classification models for heart disease prediction using feature selection and PCA. *Informatics Med. Unlocked* **2020**, *19*, 100330. [CrossRef]
24. Hassani, M.A.; Tao, R.; Kamyab, M.; Mohammadi, M.H. An approach of predicting heart disease using a hybrid neural network and decision tree. In Proceedings of the 5th International Conference on Big Data and Computing, Chengdu, China, 8–10 May 2020; pp. 84–89. [CrossRef]
25. Rajdhan, A.; Agarwal, A.; Sai, M.; Ravi, D.; Ghuli, P. Heart disease prediction using machine learning. *Int. J. Eng. Technol. IJERT* **2020**, *9*, 653–665. [CrossRef]
26. Olaniyi, E.O.; Oyedotun, O.K.; Adnan, K. Heart diseases diagnosis using neural networks arbitration. *Int. J. Intell. Syst. Appl.* **2015**, *7*, 72. [CrossRef]
27. Akinyokun, O.C.; Babatunde, I.G.; Arekete, S.; Samuel, R. Fuzzy logic-driven expert system for the diagnosis of heart failure disease. *Artif. Intell. Res.* **2015**, *4*, 12–21. [CrossRef]
28. Feshki, M.G.; Shijani, O.S. Improving the heart disease diagnosis by evolutionary algorithm of PSO and Feed Forward Neural Network. In Proceedings of the 2016 Artificial Intelligence and Robotics (IRANOPEN), Qazvin, Iran, 9 April 2016; pp. 48–53. [CrossRef]
29. Baihaqi, W.M.; Setiawan, N.A.; Ardiyanto, I. Rule extraction for fuzzy expert system to diagnose coronary artery disease. In Proceedings of the 2016 1st International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE), Grand Forks, ND, USA, 19–21 May 2016; pp. 136–141. [CrossRef]
30. Uyar, K.; İlhan, A. Diagnosis of heart disease using genetic algorithm based trained recurrent fuzzy neural networks. *Procedia Comput. Sci.* **2017**, *120*, 588–593. [CrossRef]
31. Nalluri, M.R.; Roy, D.S. Hybrid disease diagnosis using multiobjective optimization with evolutionary parameter optimization. *J. Healthc. Eng.* **2017**, *2017*, 5907264. [CrossRef]
32. Nazari, S.; Fallah, M.; Kazemipoor, H.; Salehipour, A. A fuzzy inference-fuzzy analytic hierarchy process-based clinical decision support system for diagnosis of heart diseases. *Expert Syst. Appl.* **2018**, *95*, 261–271. [CrossRef]
33. Shah, S.M.S.; Batool, S.; Khan, I.; Ashraf, M.U.; Abbas, S.H.; Hussain, S.A. Feature extraction through parallel probabilistic principal component analysis for heart disease diagnosis. *Phys. A Stat. Mech. Its Appl.* **2017**, *482*, 796–807. [CrossRef]
34. Chui, K.T.; Alhalabi, W.; Pang, S.S.H.; Pablos, P.O.d.; Liu, R.W.; Zhao, M. Disease diagnosis in smart healthcare: Innovation, technologies and applications. *Sustainability* **2017**, *9*, 2309. [CrossRef]
35. Kasbe, T.; Pippal, R.S. Design of heart disease diagnosis system using fuzzy logic. In Proceedings of the 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), Chennai, India, 1–2 August 2017; pp. 3183–3187. [CrossRef]
36. Alqudah, A.M. Fuzzy expert system for coronary heart disease diagnosis in Jordan. *Health Technol.* **2017**, *7*, 215–222. [CrossRef]
37. Pawlovsky, A.P. An ensemble based on distances for a kNN method for heart disease diagnosis. In Proceedings of the 2018 International Conference on Electronics, Information, and Communication (ICEIC), Honolulu, HI, USA, 24–27 January 2018; pp. 1–4. [CrossRef]
38. Madaan, V.; Goyal, A. X-Cardio: Fuzzy inference system to diagnose heart diseases. In Proceedings of the 2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), Greater Noida, India, 12–13 October 2018; pp. 1049–1053. [CrossRef]
39. Iancu, I. Heart disease diagnosis based on mediative fuzzy logic. *Artif. Intell. Med.* **2018**, *89*, 51–60. [CrossRef] [PubMed]

40. Kahtan, H.; Zamli, K.Z.; Fatthi, W.N.A.W.A.; Abdullah, A.; Abdulleteef, M.; Kamarulzaman, N.S. Heart disease diagnosis system using fuzzy logic. In Proceedings of the 2018 7th International Conference on Software and Computer Applications, Kuantan, Malaysia, 8–10 February 2018; pp. 297–301. [CrossRef]
41. Nourmohammadi-Khiarak, J.; Feizi-Derakhshi, M.R.; Behrouzi, K.; Mazaheri, S.; Zamani-Harghalani, Y.; Tayebi, R.M. New hybrid method for heart disease diagnosis utilizing optimization algorithm in feature selection. *Health Technol.* **2020**, *10*, 667–678. [CrossRef]
42. Jain, P.; Kaur, A. A fuzzy expert system for coronary artery disease diagnosis. In Proceedings of the Third International Conference on Advanced Informatics for Computing Research, Shimla, India, 15–16 June 2019; pp. 1–6. [CrossRef]
43. Muhammad, L.; Algehyne, E.A. Fuzzy based expert system for diagnosis of coronary artery disease in Nigeria. *Health Technol.* **2021**, *11*, 319–329. [CrossRef] [PubMed]
44. Bohacik, J.; Matiasko, K.; Benedikovic, M.; Nedeljakova, I. Algorithmic model for risk assessment of heart failure patients. In Proceedings of the 2015 IEEE 8th International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), Warsaw, Poland, 24–26 September 2015; Volume 1, pp. 177–181. [CrossRef]
45. Samuel, O.W.; Asogbon, G.M.; Sangaiah, A.K.; Fang, P.; Li, G. An integrated decision support system based on ANN and Fuzzy_AHP for heart failure risk prediction. *Expert Syst. Appl.* **2017**, *68*, 163–172. [CrossRef]
46. Jin, B.; Che, C.; Liu, Z.; Zhang, S.; Yin, X.; Wei, X. Predicting the risk of heart failure with EHR sequential data modeling. *IEEE Access* **2018**, *6*, 9256–9261. [CrossRef]
47. Driscoll, A.; Barnes, E.H.; Blankenberg, S.; Colquhoun, D.M.; Hunt, D.; Nestel, P.J.; Stewart, R.A.; West, M.J.; White, H.D.; Simes, J.; et al. Predictors of incident heart failure in patients after an acute coronary syndrome: The LIPID heart failure risk-prediction model. *Int. J. Cardiol.* **2017**, *248*, 361–368. [CrossRef]
48. Valenza, G.; Wendt, H.; Kiyono, K.; Hayano, J.; Watanabe, E.; Yamamoto, Y.; Abry, P.; Barbieri, R. Mortality prediction in severe congestive heart failure patients with multifractal point-process modeling of heartbeat dynamics. *IEEE Trans. Biomed. Eng.* **2018**, *65*, 2345–2354. [CrossRef]
49. Wang, F.; Wang, H.; Zhou, X.; Fu, R. A Driving Fatigue Feature Detection Method Based on Multifractal Theory. *IEEE Sensors J.* **2022**, *22*, 19046–19059. [CrossRef]
50. Zhang, K.; Yang, Y.; Ge, H.; Wang, J.; Lei, X.; Chen, X.; Wan, F.; Feng, H.; Tan, L. Neurogenesis and Proliferation of Neural Stem/Progenitor Cells Conferred by Artesunate via FOXO3a/p27Kip1 Axis in Mouse Stroke Model. *Mol Neurobiol.* **2022**, *59*, 4718–4729. [CrossRef]
51. Wang, Z.; Yao, L.; Li, D.; Ruan, T.; Liu, M.; Gao, J. Mortality prediction system for heart failure with orthogonal relief and dynamic radius means. *Int. J. Med. Informatics* **2018**, *115*, 10–17. [CrossRef] [PubMed]
52. Wang, B.; Bai, Y.; Yao, Z.; Li, J.; Dong, W.; Tu, Y.; Xue, W.; Tian, Y.; Wang, Y.; He, K. A multi-task neural network architecture for renal dysfunction prediction in heart failure patients with electronic health records. *IEEE Access* **2019**, *7*, 178392–178400. [CrossRef]
53. Samuel, O.W.; Yang, B.; Geng, Y.; Asogbon, M.G.; Pirbhulal, S.; Mzurikwao, D.; Idowu, O.P.; Ogundele, T.J.; Li, X.; Chen, S.; et al. A new technique for the prediction of heart failure risk driven by hierarchical neighborhood component-based learning and adaptive multi-layer networks. *Future Gener. Comput. Syst.* **2020**, *110*, 781–794. [CrossRef]
54. Yang, H.; Garibaldi, J.M. A hybrid model for automatic identification of risk factors for heart disease. *J. Biomed. Informatics* **2015**, *58*, S171–S182. [CrossRef] [PubMed]
55. Duisenbayeva, A.; Atymtayeva, L.; Beisembetov, I. Using Fuzzy logic concepts in creating the decision making expert system for cardio vascular diseases (CVD). In Proceedings of the 2016 IEEE 10th International Conference on Application of Information and Communication Technologies (AICT), Baku, Azerbaijan, 12–14 October 2016; pp. 1–5. [CrossRef]
56. Arabasadi, Z.; Alizadehsani, R.; Roshanzamir, M.; Moosaei, H.; Yarifard, A.A. Computer aided decision making for heart disease detection using hybrid neural network-Genetic algorithm. *Comput. Methods Programs Biomed.* **2017**, *141*, 19–26. [CrossRef]
57. Yazid, M.H.A.; Satria, M.H.; Talib, S.; Azman, N. Artificial neural network parameter tuning framework for heart disease classification. In Proceedings of the 2018 5th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), Malang, Indonesia, 16–18 October 2018; pp. 674–679. [CrossRef]
58. Makhlouf, A.; Boudouane, I.; Saadia, N.; Ramdane Cherif, A. Ambient assistance service for fall and heart problem detection. *J. Ambient. Intell. Humaniz. Comput.* **2019**, *10*, 1527–1546. [CrossRef]
59. Vijayashree, J.; Sultana, H.P. A machine learning framework for feature selection in heart disease classification using improved particle swarm optimization with support vector machine classifier. *Program. Comput. Softw.* **2018**, *44*, 388–397. [CrossRef]
60. Navaneeth, B.; Suchetha, M. PSO optimized 1-D CNN-SVM architecture for real-time detection and classification applications. *Comput. Biol. Med.* **2019**, *108*, 85–92. [CrossRef]
61. Kora, P.; Meenakshi, K.; Swaraja, K.; Rajani, A.; Islam, M.K. Detection of cardiac arrhythmia using fuzzy logic. *Informatics Med. Unlocked* **2019**, *17*, 100257. [CrossRef]
62. Alkhodari, M.; Fraiwan, L. Convolutional and recurrent neural networks for the detection of valvular heart diseases in phonocardiogram recordings. *Comput. Methods Programs Biomed.* **2021**, *200*, 105940. [CrossRef] [PubMed]
63. Das, S.; Pradhan, S.K.; Mishra, S.; Pradhan, S.; Pattnaik, P. Analysis of heart diseases using soft computing technique. In Proceedings of the 2021 19th OITS International Conference on Information Technology (OCIT), Bhubaneswar, India, 16–18 December 2021; pp. 178–184.

64. Das, S.; Pradhan, S.K.; Mishra, S.; Pradhan, S.; Pattnaik, P. Prediction of Heart Diseases Using Soft Computing Technique. In *Intelligent Systems: Proceedings of ICMIB 2021*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 155–167.
65. Pare, S.; Prasad, M.; Puthal, D.; Gupta, D.; Malik, A.; Saxena, A. Multilevel Color Image Segmentation using Modified Fuzzy Entropy and Cuckoo Search Algorithm. In Proceedings of the 2021 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Hyderabad, India, 7–10 July 2021; pp. 1–7. [CrossRef]
66. Prasad, M.; Er, M.J.; Lin, C.T.; Prasad, O.K.; Mohanty, M.; Singh, J. Novel Data Knowledge Representation with TSK-Type Preprocessed Collaborative Fuzzy Rule Based System. In Proceedings of the 2015 IEEE Symposium Series on Computational Intelligence, Cape Town, South Africa, 7–10 December 2015; pp. 14–21. [CrossRef]
67. Ranjbar, E.; Suratgar, A.A.; Menhaj, M.B.; Prasad, M. Design of a Fuzzy Adaptive Sliding Mode Control System for MEMS Tunable Capacitors in Voltage Reference Applications. *IEEE Trans. Fuzzy Syst.* **2022**, *30*, 1838–1852. [CrossRef]
68. Anh, N.; Prasad, M.; Srikanth, N.; Sundaram, S. Wave Forecasting using Meta-cognitive Interval Type-2 Fuzzy Inference System. *Procedia Comput. Sci.* **2018**, *144*, 33–41. [CrossRef]
69. Bharill, N.; Tiwari, A.; Malviya, A.; Patel, O.P.; Gupta, A.; Puthal, D.; Saxena, A.; Prasad, M. Fuzzy knowledge based performance analysis on big data. *Neurocomputing* **2020**, *389*, 218–228. [CrossRef]
70. Yu, Y.; Wang, L.; Ni, S.; Li, D.; Liu, J.; Chu, H.Y.; Zhang, N.; Sun, M.; Li, N.; Ren, Q.; et al. Targeting loop3 of sclerostin preserves its cardiovascular protective action and promotes bone formation. *Nat. Commun.* **2022**, *13*, 4241. [CrossRef] [PubMed]
71. Wang, L.; Yu, Y.; Ni, S.; Li, D.; Liu, J.; Xie, D.; Chu, H.Y.; Ren, Q.; Zhong, C.; Zhang, N.; et al. Therapeutic aptamer targeting sclerostin loop3 for promoting bone formation without increasing cardiovascular risk in osteogenesis imperfecta mice. *Theranostics* **2022**, *12*, 5645–5674. [CrossRef]
72. Hao, P.; Li, H.; Zhou, L.; Sun, H.; Han, J.; Zhang, Z. Serum Metal Ion-Induced Cross-Linking of Photoelectrochemical Peptides and Circulating Proteins for Evaluating Cardiac Ischemia/Reperfusion. *ACS Sens.* **2022**, *7*, 775–783. [CrossRef]
73. Zhou, L.; Liu, Y.; Sun, H.; Li, H.; Zhang, Z.; Hao, P. Usefulness of enzyme-free and enzyme-resistant detection of complement component 5 to evaluate acute myocardial infarction. *Sens. Actuators B Chem.* **2022**, *369*, 132315. [CrossRef]
74. Chawla, N.V.; Bowyer, K.W.; Hall, L.O.; Kegelmeyer, W.P. SMOTE: Synthetic minority over-sampling technique. *J. Artif. Intell. Res.* **2002**, *16*, 321–357. [CrossRef]
75. Fernández, A.; Garcia, S.; Herrera, F.; Chawla, N.V. SMOTE for learning from imbalanced data: Progress and challenges, marking the 15-year anniversary. *J. Artif. Intell. Res.* **2018**, *61*, 863–905. [CrossRef]
76. Dang, W.; Xiang, L.; Liu, S.; Yang, B.; Liu, M.; Yin, Z.; Yin, L.; Zheng, W. A Feature Matching Method based on the Convolutional Neural Network. *J. Imaging Sci. Technol.* **2023**, *13*, 030402. [CrossRef]