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# Deep learning for enhanced brain Tumor Detection and classification

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ABSTRACT

The purpose of this research is to build an automated, robust, intelligent and hybrid system for the early diagnosis and classifying of brain tumor. To serve this purpose, the authors propose the Auto Contrast Enhancer, Tumor Detector and Classifier to efficiently provide on-demand contrast improvement of poor contrast MRI images for the early diagnosis and classification of brain tumors. The classifier accomplishes its task through a two-phase approach. During the initial phase, ODTWCHE is employed to enhance image contrast, facilitating accurate diagnosis of brain tumors. In the subsequent phase, the classifier leverages the power of deep transfer learning, utilizing the pre-trained Inception V3 model to refine the diagnostic process further. tumor classification. Compared to state-of-the-art models, including AlexNet, VGG-16, DenseNet-201, VGG-19, GoogLeNet, and ResNet-50, the proposed system showcased its outstanding performance by achieving the highest accuracy of 98.89 % on a public dataset that consists of MRI images with varying contrast and brightness levels. The precise detection and classification achieved on this multicolored dataset prove the system's robustness. The authors of the article address the usage of metrics in a variety of contexts, including academia, as well as the possible problems that may result from their improper application. They emphasize how crucial it is to create measurements that align with the system's objectives and to reduce any negative consequences that can skew the data or allow people to manipulate the system's incentives. The authors provide a thorough process for creating metrics that takes into account design considerations, countermeasures for unfavorable effects, and crucial requirements. The paper provides answers for the creation of metrics and gives examples of metrics' failures in many fields. The authors emphasize the significance of understanding how the goal and the data at hand relate to one another, as well as the necessity of compromise and clarity when goals are contradictory or incoherent.A comparative analysis with existing models further confirms that the proposed system consistently outperforms the competition.

## 1. Introduction

The brain is the most important part of the human body as it is in charge of all bodily activities, such as the movement of muscles, breathing, digestion, and functionalities of sense organs [1]. A brain tumor is an unusual collection of cells that develops inside the brain as a result of unchecked rapid cell division [2]. The damaged brain region determines which area of the brain exhibits which symptoms of brain tumors. Seizures, headaches, vomiting, trouble speaking and walking, vision issues, mental health issues, and other symptoms are some of these symptoms. There are two types of brain tumors: benign and malignant [2,3]. Benign tumors are non-cancerous or non-progressive tumors that originate in the brain and grow slowly. In comparison, malignant tumors are cancerous in nature, characterized by rapid growth and ill-defined boundaries. They can infiltrate neighboring healthy cells and metastasize to distant areas of the body, including but

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not limited to bones, cartilage, muscles, blood vessels, and the digestive system [1].

Various types of brain tumors can have detrimental effects on the brain's operational efficiency, decision-making processes, and overall control abilities [4,5]. Consequently, such tumors pose a significant threat to an individual's life. Notably, brain tumors are responsible for causing 85–90 % of central nervous system damage among all health conditions [4]. Tragically, brain and CNS malignancies rank as the tenth leading cause of death worldwide [1,4]. In 2020 alone, an estimated 18, 020 adults, comprising 10,190 men and 7830 women, succumbed to brain cancer [4]. Furthermore, the survival rate of patients diminishes with age. The 5-year survival rate stands at approximately 74 % for individuals under the age of 15, declining to 71 % for those aged 15 to 39, and dropping significantly to 21 % for individuals over 40 years of age. A report by the World Health Organization (WHO) [4] highlights a substantial global increase in the number of brain tumor cases. In 2020, 23,890 adults in the United States, including 13,590 males and 10,300 females, were diagnosed with malignant brain and spinal cord tumors. Additionally, in 2021, 3540 children under the age of 15 were diagnosed with brain tumors [1]. This alarming rise in brain tumor cases and related fatalities worldwide underscores the pressing need for a novel system capable of early detection, classification, and severity assessment of brain tumors.

In the modern era, MRI is a widely used modality for analyzing and classifying brain tumors. Radiologists categorize brain tumors as healthy or tumorous based on MRI scans. Subsequently, tumorous brain tumors can be further classified into different categories. However, this manual assessment of brain tumor is non-reproducible and time-consuming. Additionally, it becomes hard for radiologists to analyze and classify tumors from low-contrast MRI images because of the non-homogenous power dissemination around the tumorous cells and the presence of background noise. Further, the manual screening of a large number of MRI images captured at hospitals increases the burden on health experts, leading to greater wait times for diagnosing a disease.

Recognizing these challenges, the authors of references [5,2] have taken steps such as cascaded V-Nets structure, ensemble strategy, and focal loss to address them by developing computer-assisted systems for the segmentation, detection, diagnosis, and classification of tumors. It is important to note, however, that these systems are designed to process contrast-enhanced MRI brain images as their input. Additionally, the authors of reference [3] have emphasized the significance of Deep Learning (DL) and Machine Learning (ML) techniques in the realm of computer-assisted brain image analysis. These techniques play a crucial role in image registration, segmentation, feature extraction, and tumor classification tasks. They highlight that DL models possess multiple layers that can be trained using both unsupervised and supervised methods to make predictions based on available datasets. Notably, DL models like Convolutional Neural Networks (CNNs) excel at automatically extracting high- and low-level features from MRI images. As a result, they have been successfully employed in accurately detecting and classifying various diseases across a range of clinical applications [4,2].

Researchers have been motivated by the challenges of manually reading MRIs and the efficacy of DL techniques in automating disease diagnosis and classification. In such studies, image processing, computer vision, deep learning, machine learning, and object detection have been adopted to develop systems for assisting health experts in the early diagnosis of brain tumors.

However, models employing Convolutional Neural Networks (CNN) and their variations have struggled to achieve substantial enhancements in performance. Despite previous attempts, there remains a noticeable gap in the development of a precise implementation tailored to enhance low-contrast brain MRI images, particularly when dealing with limited available data [2]. While deep learning techniques, such as CNNs, have yielded remarkable results in various fields, they are often data-hungry, typically requiring a significant number of training samples. Consequently, the challenge of creating an effective, integrated system for contrast enhancement, tumor detection, and classification, even with a limited training dataset remains an open problem.

To address this challenge, transfer learning can be utilized to adjust the all-around acquired substantial information with the data to be received from the small dataset. Finding edges at the lowest levels, forms in the intermediate layer, and specific task-specific traits in the upper layers are the main objectives of neural networks. In transfer learning, only the later layers are retrained; the early and intermediate layers are used. It makes use of the task's labeled data from its first training. In transfer learning, we attempt to transfer as much information as we can from the task the model was trained on earlier to the current task. Depending on the issue and the available information, this knowledge might take on several forms. Although there are many advantages to transfer learning, the three primary ones are reduced training time, improved neural network performance (most of the time), and fewer resource requirements.

The network is trained with a small dataset comprised of MRI images of tumorous and healthy brains. The network uses the previously gained information about the high-level features, like shape, color, and size, from this dataset to efficiently identify and classify a tumor.

In this paper, the researchers address all of the previously mentioned difficulties by fostering a computer-aided diagnosis (CAD) framework for low-contrast brain MRI image enhancement as well as tumor identification and classification. The proposed system employs the ODTWCHE technique [3] for contrast improvement of brain MRI images. This strategy automatically selects an optimal value of threshold for image division and effectively enhances the contrast by preserving most of the details recorded in an image. CNN automatically extracts all essential features from brain MRI and becomes proficient in tumor identification and classification.

The key contributions of this research are as follows.

- Conducts a comprehensive, in-depth assessment of the pivotal factors intertwined with deep transfer learning, and how they impact the fine-tuning of pre-trained models, examining the subject from a top-to-bottom perspective.
- Integrates contrast enhancement techniques with deep transfer learning for brain tumor diagnosis and classification.
- Develops a robust structure for automated identification and classification of brain tumors.
- Presents a comparative analysis of the performance of popular deep convolutional neural networks, including AlexNet, GoogLeNet, Dense Net, VGG Net and ResNet, on the same dataset comprising MRI images of the brain.

The remaining sections of the paper is organized as follows. The related research on the identification and classification of brain tumors is discussed in Section 2. The two-stage multi-model framework for contrast improvement, tumor diagnosis, and classification is described in Section 3, along with its design and implementation. Section 4 contains documentation of the experimental findings and simulations used to evaluate the effectiveness of the entire diagnosis framework. Section 5 presents the final observations and recommendations for the future.

## 2. Related works

Research on recognizing and classifying of brain tumors from MRI images remains very active. Numerous methods have been introduced in the last 20 years [6–12], offering solutions for this crucial task. These methods have evolved significantly, moving from traditional machine learning algorithms [6–10] to more refined deep learning models [11–31].

For example, the researchers in Ref. [32] proposed a mixed approach for categorization and segmentation that consists of three phases. The model's accuracy, sensitivity, and specificity were assured by the researchers to be 96.34 %, 93.47 %, and 100 %, respectively.

The authors of [33] used a grouping of Berkeley Wavelet Transform-based brain tumor division and SVM as a classifier tool to modify the diagnostic precision. They employed a GLCM technique for the extraction of the texture of brain tumors. Their model achieved a specificity of 94.2 %, accuracy of 96.51 %, and average value of dice similarity index coefficient of 0.82. This model reported an improvement of 4.25 % in the sensitivity for the brain tumor classification [6].

Before using Fuzzy C-Means (FCM) for segmentation, the authors of [6] preprocessed images using a Gaussian filter in order to increase the accuracy of tumor detection and classification. Curvelet transform was used for feature extraction, and probabilistic neural networks were used to classify tumors. According to the paper, the suggested method identified tumors with 98 % accuracy.

A model that preprocesses, segments, and classifies input brain tumor MRI images was created by the authors of [7]. Morphological operation, median filter, feature extraction, masking, and SVM-based classification are all included in their model. They claimed to have classified malignant tumors with 99 % accuracy.

The authors of [8] focused on noise removal strategies, GLCM-based feature extraction, and Discrete Wavelet Transform (DWT)-based brain tumor region growing division for improved performance and reduced time consumption. They utilized morphological filtering and PNN for tumor classification. The authors asserted that their approach was 100 % accurate at differentiating between normal and abnormal tissues in brain MRI images.

In the realm of ML-based automated tumor detection techniques [6–10], the current state-of-the-art predominantly highlights two primary challenges associated with feature extraction. The first challenge pertains to the exclusive focus on either high-level or low-level features by these techniques. The second challenge involves the reliance on handcrafted features, necessitating human intervention and considerable effort for the extraction and categorization of statistical and structural features. Furthermore, conventional ML models and algorithms [7,9] require domain-specific knowledge and expertise. Insufficient expertise in the domain and biased decision-making can potentially undermine the efficiency and accuracy of the system.

To address these challenges, there is a strong requirement for a robust automated CAD system for the detection and classification of brain tumors. The deep transfer learning strategies play a coherent role in the extraction of discriminative and visual features utilizing different convolutional layers [16,17]. These extracted learning features make the framework powerful for the classification of diseases.

The effectiveness of AlexNet, VGG Net, and GoogLeNet in classifying brain tumors from various datasets was compared by the researchers in Ref. [9]. In order to reduce the possibility of over-fitting and increase the dataset's sample sizes, they employed data augmentation techniques. To maximize the performance of the DL models, they also adjusted the weights of the neurons and froze various network layers. The findings led the authors to conclude that VGG-16 performed better in identifying and categorizing brain tumors, with an accuracy of up to 98.69 %.

A block-wise fine-tuning method based on transfer learning that does not require handcrafted features and requires little preprocessing was proposed by the authors of [10]. Using five-fold cross-validation, it obtained an average accuracy of 94.82 %. A different study [11] suggested a deep transfer learning-based classification system that extracts features from MRI images of brain tumors by using a pre-trained GoogLeNet model. With five-fold cross-validation, the suggested system was able to attain a mean classification accuracy of 98 % on a publicly accessible dataset [13] that contained brain MRI images. The authors ensured that transfer learning is a useful technique when a limited dataset is available for model training based on the outcomes in the simulated environment.

The authors of [12] developed an automatic system for detection and classification of brain tumors, which employs a Gaussian filter for preprocessing brain MRI images, AlexNet and VGG-16 for deep feature extraction, and Extreme Learning Machine (ELM) classifier for classification. They utilized CNN models on three datasets, namely 'The Cancer Imaging Archive' (TCIA) [19], 'Fig share brain tumor dataset' [13] and 'Rembrandt dataset' [19] for extracting feature vectors. Based on the simulation results, the authors claimed that their model has a higher accuracy of 97.44 % compared to content-based image retrieval (CBIR), support vector machine (SVM), and boosted decision tree (BDT) methods [12].

The researchers in Ref. [14] utilized the ResNet-50 model to diagnose brain cancers by analyzing brain MRI images. According to their research, this model is automated and obtained a classification accuracy of 97.2 % in identifying brain tumors. In addition, their model addresses the constraints of previously documented techniques [2,3,5–7,32,33] that necessitate the manual outlining of tumor zones before categorization. Nevertheless, the model suggested in Ref. [14] exhibited subpar performance when applied to the imbalanced dataset 'TCIA' [19]. In order to enhance the detection and categorization of cancers, the authors of [15] proposed a two-phase multi-model approach for the automatic diagnosis of brain tumors. The initial stage utilizes the Error-Correcting Output Codes Support Vector Machine (ECOC-SVM) for the purposes of preprocessing, feature extraction, and feature categorization. The system utilizes CNN models, such as VGG-16, AlexNet, and VGG-19, to classify brain tumors into abnormal and normal categories. Among the three models, the AlexNet model attained the highest accuracy of 99.55 %. The second stage of the system employs the Region-based Convolutional Neural Network (R–CNN) to accurately identify the location of a tumor in brain MRI scans. This model achieved a dice score of 0.87, providing evidence of its efficiency. The authors of reference [21] presented a Subtractive Spatial Lightweight Convolutional Neural Network (SSLW-CNN) model in their research. This model adds new operators targeted at lowering the complexity of categorization and is applied to MR-based brain pictures. Notably, the model also incorporates Class Activation Mapping (CAM) to enhance the comprehensibility of the background. Evaluating the confidence level of the model's success is a crucial component of this research.

In [29], authors proposed a hybrid and efficient 3D model for brain tumor segmentation. It integrates the strengths of deep learning models V-Net and 3DU-Net by effectively extracting the features from their encoders. After that, a 3D convolution layer and Transformers block are added for more information, and a concatenation between these features and their fusion is performed at each decoder depth to create new noteworthy features. Furthermore, a final convolution block is performed to obtain the segmented tumour. The researchers of [22,31] comprehensively reviewed the different types of DL techniques and reported that many models exhibit a highly domain-specific efficiency and could be trained by two or more methods. In both papers, the authors clearly suggest that hybrid conventional DL models are more efficient in overcoming the problems that occur in conventional DL models. The authors of [23] briefly review different standard machine learning techniques in the medical field. This survey mainly covers the five major ML models in the medical field to solve the problems of medical imaging, wearable sensors, medical chemistry, brain & other treatments. The paper also presents valuable guidance and references for decision-makers to plan future research and development directions. Further, researchers of [24] thoroughly reviewed multimodal medical image fusion methodologies, databases, and quality measurements. The authors of [25] proposed a novel technique for extracting and classifying tumor features in 3D brain slice images.

The empirical work done in the literature shows that DL techniques outperform ML approaches in identifying and classifying tumors. Fig. 1 presents a timeline of the different methods employed for brain tumor identification and classification from 2017 to 2020.

## 3. Proposed work

In this study endeavor, the scientists built an automated, intelligent and robust brain tumor recognition and classification system. This

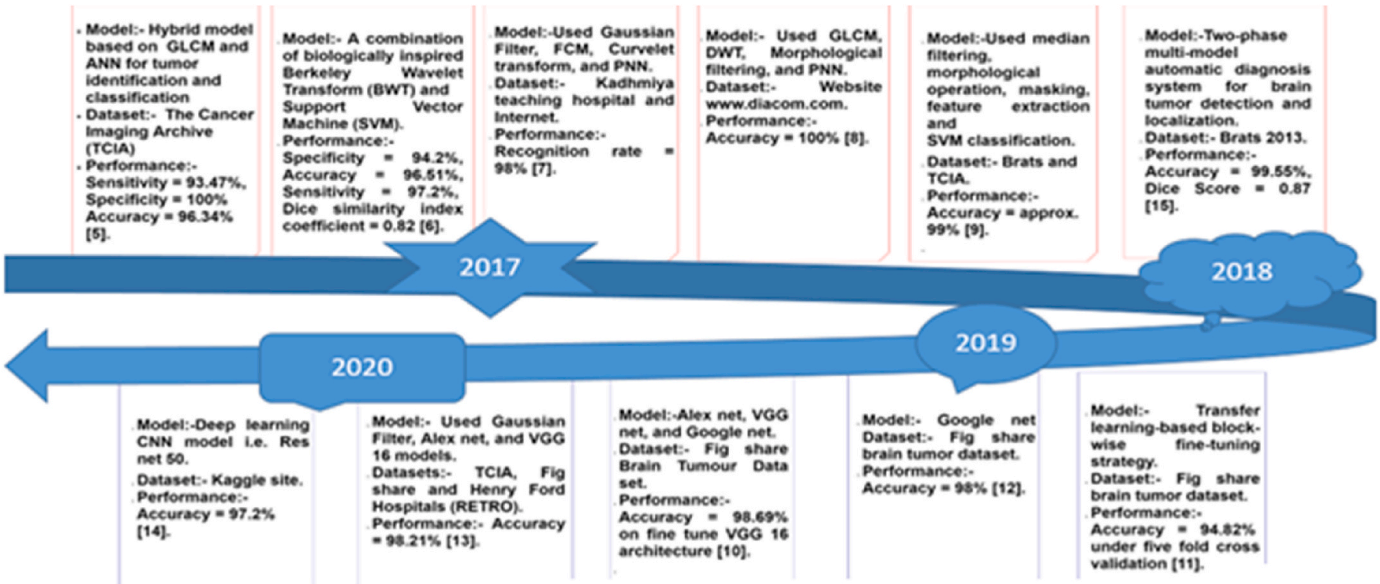


**Fig. 1.** Timeline of brain tumor detection and classification techniques.

computer-assisted analytical system completes its duty in two steps, as depicted in Fig. 2. The first step applies the ODTWCHE for preparing poor contrast medical MRI images [3]. In this phase, the system measures the contrast of the incoming MRI pictures. If the contrast of an MRI image is lower than the pre-set threshold, then it does the contrast enhancement. This phase intelligently minimizes the problem of over-enhancing and also saves computation time by ignoring the contrast enhancement of good quality MRI. In this phase, the image-specific contrast enhancement technique is followed by brain tumor detection. The second step of the architecture employs deep transfer learning for the classification of tumors into malignant and benign categories. This stage applies a pre-trained inspection V3 model to consequently remove all low-level and significant-level characteristics from brain MRI images.

### 3.1. First phase: image preprocessing

The authors chose the MRI modality for brain tumor detection and classification in this research because these images provide detailed info about the brain soft tissues. However, identifying and localizing a tumor are hindered by the poor visual quality, noise, and low contrast of these images. Therefore, the authors employed the preprocessing technique 'ODTWCHE' to improve visual quality, lessen the level of noise, and enhance the contrast [3]. This technique, shown in Fig. 3, augments the quality of MRI images and preserves the maximum information encoded in the MRI. Further, the authors also applied data augmentation techniques, such as rotation and flipping, to upsurge the size of the dataset. In rotation, the input images are rotated at angles of 90°, 180°, and 270°, whereas the input image is reflected from horizontal and vertical directions via flipping [16]. The augmentation techniques are useful in providing a large input space to CNNs and reducing the problem of overfitting [30].

The ODTWCHE technique involves the following six steps to complete the preprocessing of brain MRI images [3]:

In the initial stage, Otsu's double threshold method is applied to segment the input image histogram into three separate sub-histograms: target, background, and foreground. This method does global thresholding by taking into account the histogram's shape and automatically determines the appropriate threshold value by maximizing the variation between classes. Consequently, it has shown to be an excellent strategy for segmenting histograms, even in circumstances with complex backgrounds and photos with many objects.

The method uses the weighted normalized constrained model to do the probability adjustment of statistical sub-histograms in the second stage. With this method, weights are assigned more heavily to fewer successive grey levels and less heavily to more successive grey levels. Consequently, it effectively reduces the dominance of high-frequency histogram bins and manages the issue of excessive amplification.

The weighted normalized constrained model's ideal parameter value is determined in the third stage using Particle Swarm Optimization

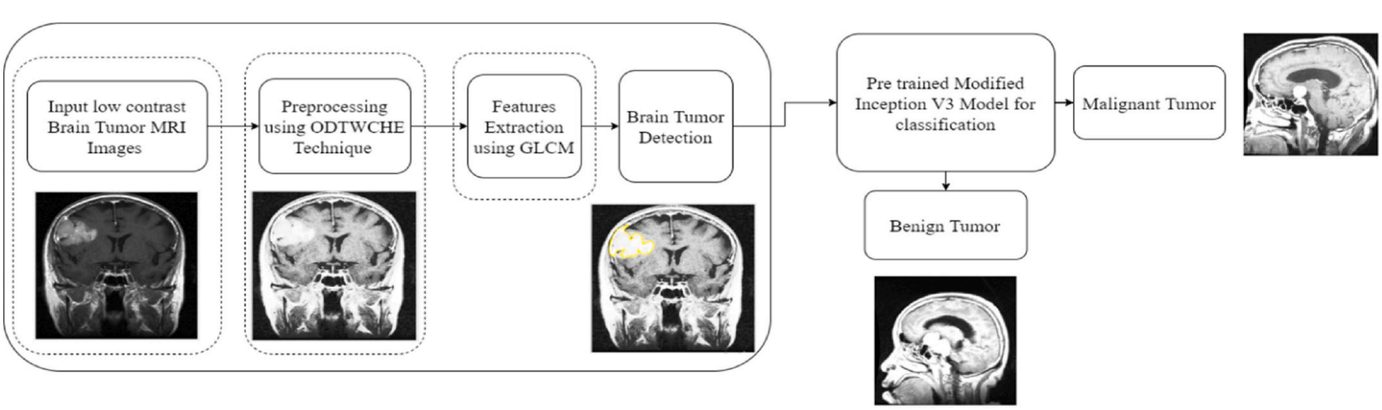


**Fig. 2.** Architecture of Auto contrast enhancer, tumor detector and classifier.

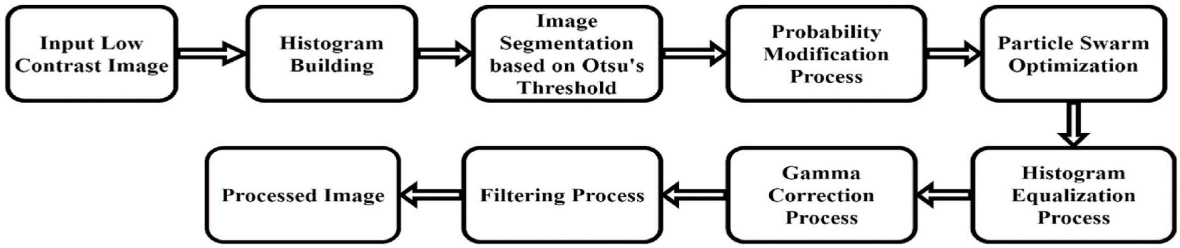


**Fig. 3.** Block diagram of ODTWCHE technique.

(PSO). PSO's simplicity, quickness, and low processing cost make it beneficial in many various circumstances [26]. This approach uses a collection of particles to achieve the ideal response. These particles are distributed over the solution space like a swarm. Position and velocity are the two vectors that each particle employs. In order to manage the degree of augmentation and preserve more information, this strategy uses the fitness function as entropy. The fitness value of each particle is determined with respect to its location [26].

In the fourth step, the histogram equalization method equalizes all sub-histograms independently. Based on the transformation function, it distributes the intensity values over the entire scope of an input image. It develops the histogram with consistent power dissemination and improves the contrast of an input image [3].

The adaptive gamma correction process is used in the fifth stage to further enhance the global contrast of an equalized picture. This method maintains a balance between reduced computational cost and enhanced visual quality. It avoids a crucial drop in high-intensity values while actually building low-intensity values. It also stays well away from any abnormal alterations that take place in the Cumulative Density Function (also known as the CDF) function.

Wiener filtering is used as a last resort to reduce noise in visually significant areas of an improved picture. An algorithm that restricts the Mean Square Error (MSE) between an original picture and a comparable reconstructed image is called the Wiener filter. It operates in linear space. The wiener filter has two parts to its filtering process: noise smoothing using a compression operator and inverse filtering for deconvolution. This filtering, therefore, delivers the best feasible trade-off between noise and inverse filtering. The preprocessed brain MRI image is beneficial for tumor identification and categorization.

#### 3.1.1. *Evaluation of performance of ODTWCHE technique*

The 3064 low-contrast MRI images of a tumorous brain that are part of the publicly available Fig share dataset [13] were utilized by the authors to evaluate the efficacy of the proposed ODTWCHE approach. A personal computer running Windows 10 with an Intel Core i3 platform, 2.0 GHz processor, and 32 GB RAM was used for the experiments. The suggested preprocessing method's performance in a simulated environment was assessed using MATLAB software R2017a. Several criteria, including entropy, contrast, and Peak Signal Noise Ratio (PSNR), as described in Ref. [3], were used to assess ODTWCHE's performance.

The experimental results in Fig. 4 display that the suggested technique yielded an average entropy of 7.32 bits. This value is equivalent to the entropy of the original input image. Furthermore, this technique produced minimum saturation effects of intensities. An average PSNR value of 29.07 DB and regular contrast of 39.47 DB was also determined. These PSNR and contrast values are higher than those attained by the existing techniques, such as GHE, BBHE, AGCWD, DSIHE, RLDTMHE, RLBHE, TOHE and EASHE [3]. Subsequently, it demonstrates that ODTWCHE can more effectively improve contrast, preserve brightness, and avoid undesirable visual artifacts [3]. The comparison of the ODTWCHE technique with the stated existing techniques proves its supremacy.

### 3.2. *Second phase*

#### 3.2.1. *Features extraction and Tumor Detection using deep transfer learning*

The GLCM technique [17] was utilized by the authors in this stage to extract the textual and statistical information from the MRI images. Tumour detection is aided by the differences in the values of statistical features for the tumorous and non-tumorous cells, such as the centroid, area, major axis length, bounding box, eccentricity, minor axis length, orientation, filled area, convex area, equivalent diameter, solidity, extent, and perimeter. ability to distinguish between tumorous and non-tumorous tissues is further aided by textural features such as contrast, entropy, correlation, Inverse difference moment, sum entropy, variance, sum average, inertia, cluster prominence, difference entropy, homogeneity, cluster shade, dissimilarity, energy, autocorrelation, maximum probability, and inverse difference normalized (INN) from the preprocessed brain MRI. Data pertaining to the textural and statistical characteristics of cancerous cells are essential for brain tumor identification, tumour severity assessment, and evaluation of the patient's body's reaction to treatment.

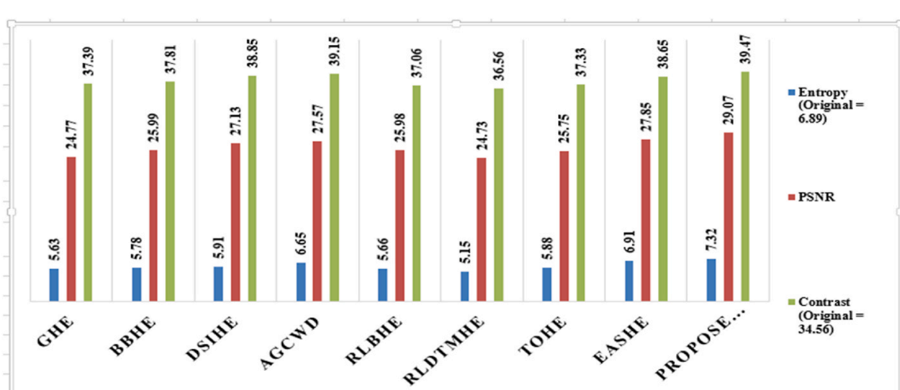


**Fig. 4.** Entropy, PSNR, and contrast for MRI images.

#### 3.2.2. Tumor Detection phase

The research's suggested approach successfully identified the tumour in its early stages. Using MATLAB's built-in "bwlabeln " function, the approach transforms the preprocessed output picture into binary format during the first step, called "Image Processing". The authors of this research suggest a preprocessing method that works just on a portion of the image, not on the entire image. This approach reduces computation time and fixes overfitting issues in a Cascade Deep Learning model. The suggested model uses two distinct approaches to mine both local and global characteristics. So, all the connected components that are less than 50 pixels are removed [28]. Further, it segments the image and isolates the tumor from the skull and other tissues of brain, isolating the tumorous tissues based on solidity and area values [20]. Experimental MRI Images of the brain and skull are shown in Figs. 5–8, obtained from the Figshare database. A recognized and well-known generalist repository, Figshare facilitates the FAIR and citable sharing of research data supported by the National Institutes of Health. It fits most of the NIH's ideal features for data repositories and can be used in combination with discipline-specific repositories to share various types of research outputs. As part of their Generalist Repository Ecosystem Initiative, Figshare and the NIH are now collaborating to further improve support for the needs of NIH-funded researchers. This is the clear link of selecting the Figshare dataset in this research work.

In view of the exploratory outcomes, the authors guarantee the viability of the proposed framework in the detection of a brain tumor at the beginning phase. The accurate and precise determination of a brain tumor at the beginning phase is highly valuable to reduce the risk of obtrusive medical procedures and expand the number of therapy choices [28]. In this way, it helps to monitor the patients while working on resilience.

### 3.3. Brain tumor classification phase

In the second phase, VGG-16, VGG-19, Dense Net-201, ResNet-50, and Inception V3 models are employed to classify brain tumor into malignant and benign. A comparison of these models showed that Inception V3 outperforms the others on the same dataset [13] of brain MRI images. Therefore, the authors adopted the Inception V3 model as a classifier in the Auto Contrast Enhancer, Tumor Detector and Classifier. They also fine-tuned the models according to the type and size of the dataset and desired outputs. The architecture of the Inception V3 model is illustrated in Fig. 9. This model receives the input image and performs different operations, such as convolution, pooling, activation, dropout, flattening, etc., at various layers. All of these layers are subsequently described in more detail.

This work also examines the implications of deep learning techniques for medicine and healthcare while considering current studies on their interpretability and explainability. We give particular emphasis to one method that data and model visualization might be used to address interpretability and explainability in this setting. We contend that including medical specialists in the design of data analysis interpretation techniques is necessary, in addition to aiming to improve model interpretability as a standalone goal. If not, deep learning is unlikely to find its way into standard clinical and medical procedures.

- **Convolutional Layer**

The Inception V3 model employed in the Auto Contrast Enhancer, Tumor Detector and Classifier is a deep convolution neural network comprising 94 convolution layers. Each convolution layer receives the input image in the form of a matrix. It conducts the convolution operation and produces the feature maps of the input image. The convolution is a linear operation described in Equation (1), in which w and x are the previous layer inputs, m x n is the convolutional matrix size, and y is the result of the convolutional layer. The first convolution layer contains the kernel with 11 × 11 × 3 dimensions. The remaining 93 convolution layers contain kernels of 5 x 5 x 48 dimensions [27].

$$y(i,j) = x(i,j) * w(i,j) = \sum_m \sum_m x(m,n)\, w(i-m, j-n) \tag{1}$$

- **Activation Function**

In multilayer artificial neural networks or deep neural networks, activation functions like Sigmoid, Tanh, and ReLU [14] are used for nonlinear transformations of the values obtained by the convolution operation. In the proposed model, the authors employed the ReLu activation function, as defined in Equation (2). This function overcomes the problem of vanishing gradient, which arises due to the degradation of weights to infinitesimal minimum in a deep neural network. The negligible weights lead to difficulty in converging the model and reaching the optimal solution.

$$Relu : f(y) = \begin{cases} 0, y < 0 \\ 1, y \geq 0 \end{cases} \tag{2}$$

- **Batch Normalization**

Batch normalization is applied to normalize the convolution outputs, which is important for quick training of the network and reducing the covariance shift [15]. Its definition is given in Equation (3), in which $M$ is the number of input data items, $\mu_\beta$ is the average value of the stack, $Y_i$ are the resulting values obtained from the normalization process, and $\sigma_\beta$ is the standard deviation of the stack.

$$Y_i = \frac{X_i - \mu_\beta}{\sqrt{\sigma_\beta^2 + \in}} \tag{3}$$

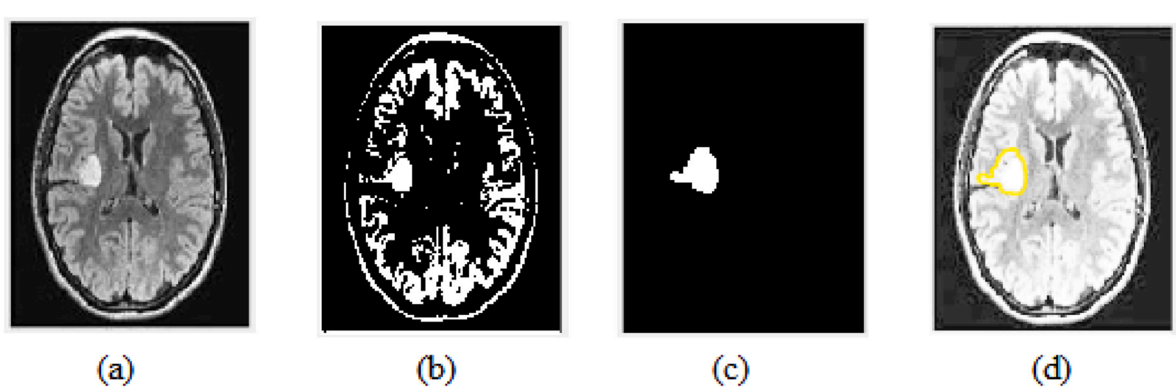


**Fig. 5.** Example 1 of tumor detection in brain MRI image: (a) original image, (b) twofold image, (c) identified tumor, and (d) improved image with detected tumor.

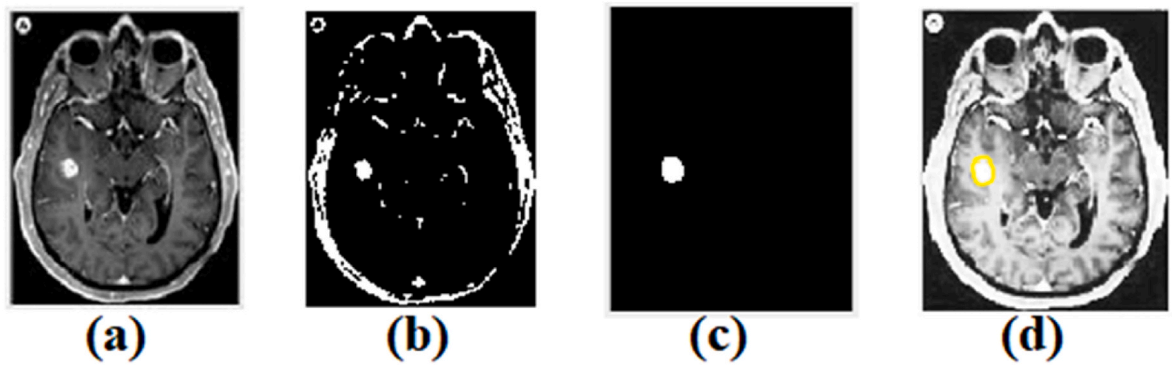

**Fig. 6.** Example 2 of tumor detection in brain MRI image: (a) original image, (b) twofold image, (c) identified tumor, and (d) improved image with detected tumor.

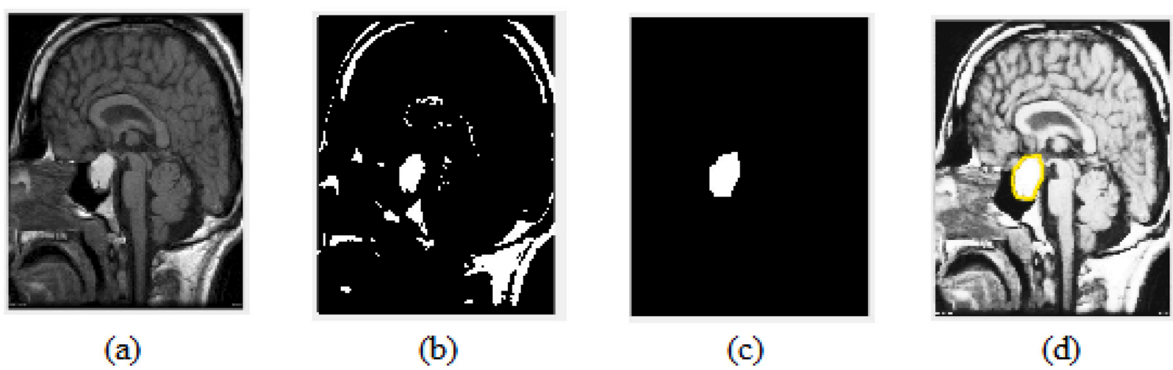

**Fig. 7.** Example 1 of tumor detection in skull MRI image: (a) original image, (b) twofold image, (c) identified tumor, and (d) improved image with detected tumor.

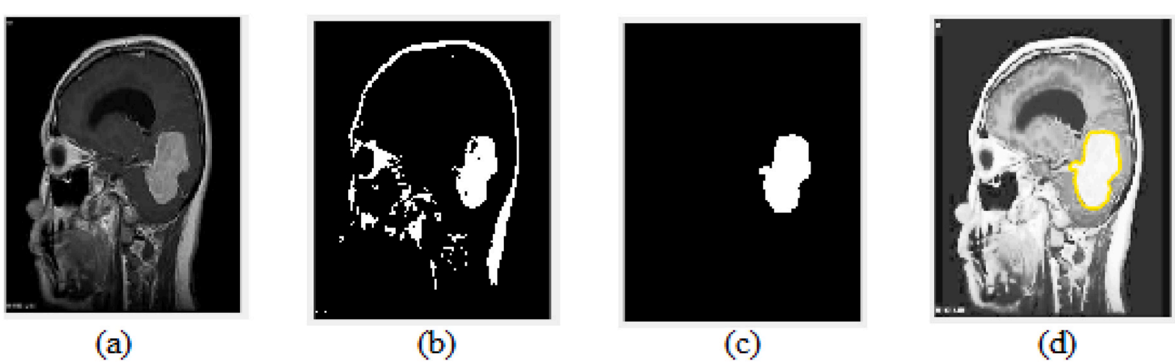

**Fig. 8.** Example 2 of tumor detection in skull MRI image: (a) original image, (b) twofold image, (c) identified tumor, and (d) improved image with detected tumor.

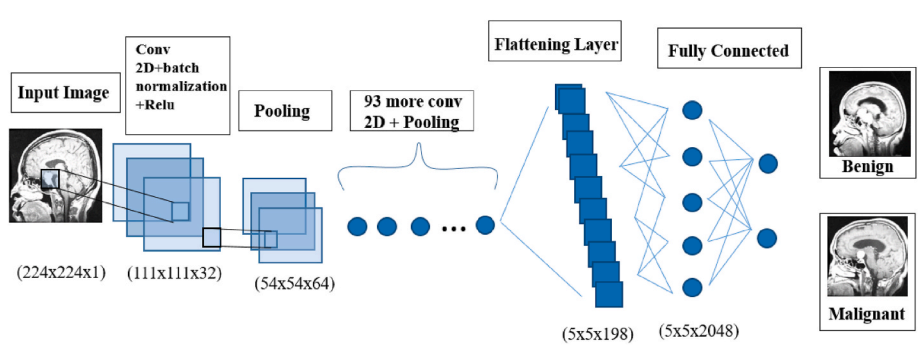


**Fig. 9.** Architecture of the Inception V3 model.

Here, $\sigma_{\beta=}\frac{1}{M}\sum_{i=1}^{M}(X_i-\mu_\beta)^2$ and $\mu_\beta=\frac{1}{M}\sum_{i=1}^{M}X_i$ ; i = 1, 2 ….M

- **Pooling Layer**

The information supplied in the convolutional layer's output is made simpler by this layer. It creates a summary feature map after receiving each feature map that the convolutional layer produced. In deep convolution neural networks, max and average pooling are commonly utilized pooling layers [5]. The authors included a max-pooling layer with a filter size of N × N, where N equals three, in the proposed model.

Equation (4) is used to calculate the dimension of the output image obtained after applying the pooling operation.

$$S = w2 * h2 * d2 \tag{4}$$

Here, $w2=\frac{(w1-f)}{A+1}$ $h2=\frac{h1-f}{A+1}$ $d2\ = d1$.where $h1$ is the height; $w1$ is the width; $d1$ is the value of depth of the input image; $f$ is the filter size; $A$ is the number of steps used; and $S$ is the size of the resultant image.

- **Flattening Layer**

This layer is used to convert the multidimensional outputs obtained from the previous layer to the one-dimensional array. This is important to establish a connection between the neurons and the next layer.

- **Dropout Layer**

This layer is employed to prevent the network from overlearning by randomly dropping the connections during training. To minimize overfitting, it is generally recommended to obtain the mean forecasts from every potential parameter configuration and combine the resulting data. However, this becomes too computationally costly and is not practical for a real-time prediction or inference. The alternative method uses numerous neural networks with various topologies and is influenced by ensemble techniques (e.g., AdaBoost, XGBoost, Random Forest). However, this calls for the training and storing of many models, which eventually becomes a challenging task as the networks become deeper.

Thus, Dropout Layers provide an ideal option. Selecting nodes to be dropped out with a specific probability (e.g., 20 %) in each weight update cycle makes dropout simple to implement [27]. Thus, in this research, the authors used a dropout of 0.2. It is significant to note that the dropout layer is not used for testing and validation of the model.

- **Fully Connected Layer**

After features are extracted, the neural network's Fully Connected (FC) layer is essential for grouping the input into distinct categories. Every neuron in the fully linked layer is dependent upon the prior layer's design. The neurons in the preceding layer can choose to link to the neurons in the following layer one-to-one using this layer. In the feed-forward network, the completely linked layer is specified by Equation (5) [14].

$$u_i^n = \sum_j w_{ji}^{n-1} y_j^{n-1} \tag{5}$$

$$y_i^n = f(u_i^n) + b^{(n)} \tag{6}$$

where w_jiˆ(n-1) is the weight of neurons in the hidden layer, y_jˆ(n-1) is the value of input neurons, u_iˆn is the value of the resultant layer used before the activation function, and bˆ((n)) is the deviation value. Additionally, $n$ is the total number of layers, i,j is the number of neurons, and y_iˆn is the value in the resultant layer created.

## 4. Results and discussion

### 4.1. Dataset

In order to evaluate the effectiveness of the suggested strategy, the authors of this work employed the publicly accessible Fig sharing database [13]. This collection, which was created by Cheng in 2017, includes 397 brain MRI photos from 233 different people as the testing dataset and 3064 brain MRI photographs as the training dataset. Additionally, MRI images of individuals with benign and/or malignant brain tumors are included in the collection. These images, which include coronal, axial, and sagittal views, are all related to the T1-CE-MRI modality. A training dataset of 735 MRI images and a testing dataset of 219 MRI images make up the benign tumour dataset. There are 2284 MRI images of malignant tumors in the training dataset and 178 MRI images in the testing dataset. Table 1 provides an explanation of the quantity of various types of MRI images. Fig. 10 displays the samples of MRI images that were used to carry out the tests in this study.

### 4.2. Evaluation metrics

Classification accuracy is a compelling measure to describe the performance of a model when an equivalent number of samples from every class are available in the test datasets. However, the proposed system was evaluated on the Fig share dataset [13], which contains different numbers of benign and malignant tumor images. This yields inevitability for additional assessment of the proposed model with more performance measurement parameters. In this sequence, the authors used the confusion matrix to prove the reliability of the performance of the Auto Contrast Enhancer, Tumor Detector and Classifier for tumor classification. The confusion matrix summarizes the number of correct and incorrect classifications of the test dataset, as shown in Table 2. Here, TB is the quantity of accurately characterized tests of Benign tumors; TM is the quantity of accurately classified samples of Malignant tumors; FB presents the number of samples of Benign tumors that are misclassified as Malignant; and FM is the number of samples of Benign tumors that are classified as Malignant. Based on the information recorded in the confusion matrix, the authors defined the evaluation metrics given below.

### 4.3. Sensitivity for benign tumor

$Sensitivity_B$ is the measure of correct classifications of Benign tumors from the total number of tumor samples and is defined in Equation (7):

$$Sensitivity_B = \frac{TB}{TB+FM} \tag{7}$$

### 4.4. Sensitivity for malignant tumor

$Sensitivity_M$ is the measure of correct classifications of samples of Malignant tumors from the total number of tumor samples used for experiments, which is defined in Equation (8):

$$Sensitivity_M = \frac{TM}{TM+TB} \tag{8}$$

**Table 1**
Information on the testing and training datasets that are used to classify and identify tumors.

| Images Count | Trained Dataset | | Tested Dataset | |
|---|---|---|---|---|
| | Benign | Malignant | Benign | Malignant |
| 3064 | 561 | 2106 | 219 | 178 |

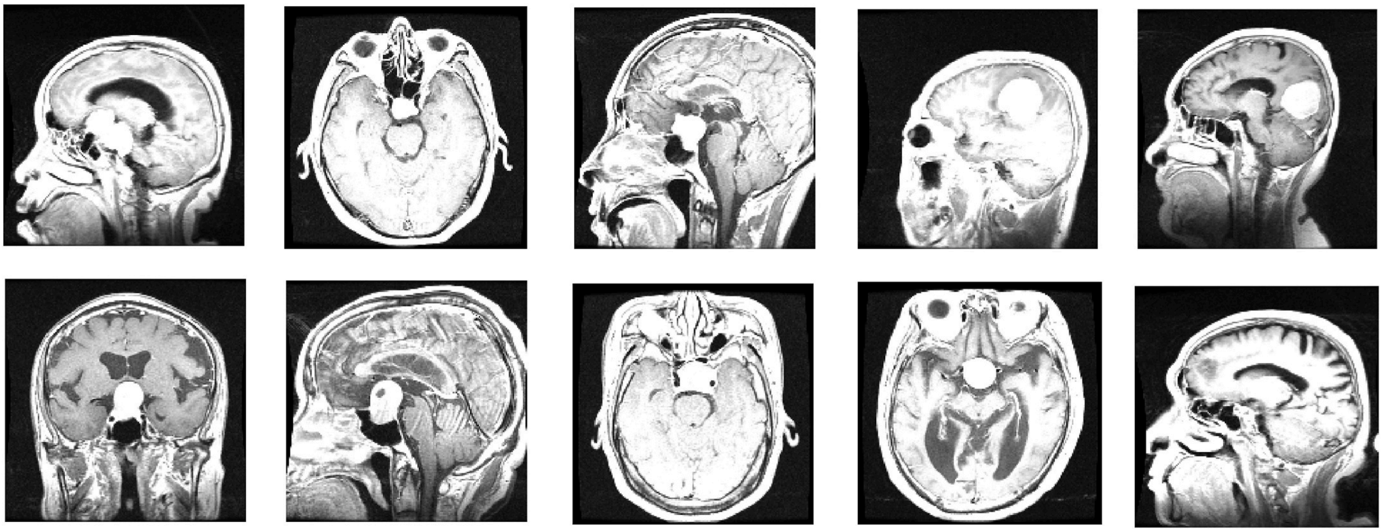

**Fig. 10.** Samples of MRI images from the Fig share database [13]: benign tumor on top row and malignant tumor on bottom row.

**Table 2**
Confusion matrix.

| | Benign | Malignant |
|---|---|---|
| Benign | 215 (TB) | 1(FB) |
| Malignant | 4 (FM) | 177(TM) |

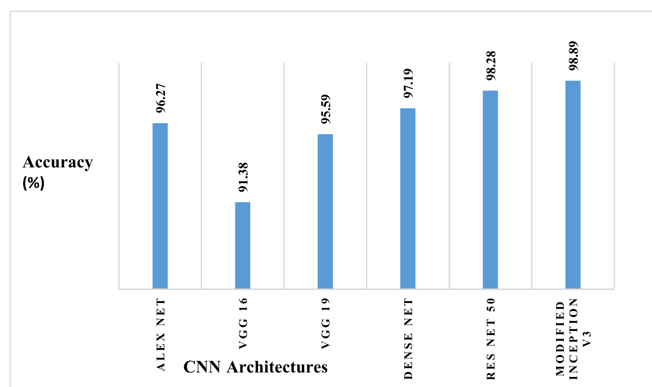


**Fig. 11.** Comparison of accuracy achieved by CNN architectures for tumor classification.

### 4.5. Accuracy

Accuracy is the measure of the total number of correct classifications from the total number of samples used for experiments [11], which is given as follows:

$$Accuracy = \frac{TB + TM}{TB + TM + FB + FM} \tag{9}$$

### 4.6. Experiments results

The authors employed CNN architectures, viz. AlexNet, VGG-16, VGG-19, Dense Net-201, ResNet-50 and Inception V3, for the classification of tumors into malignant and benign classes. They also pre-set the values of the parameters based on the set of experiments and the values reported in the related works [16,17]. The values of different model's parameters are shown in Table 3. The number of features and parameters in a CNN architecture depends on the network's depth and the number of convolutional and fully connected layers. Therefore, the performance of these models varies even for the same values of the parameters given in Table 3. To achieve the optimal performance of the above-stated models, these models were executed for 30 epochs. In order to prevent overfitting and give the model enough training time to converge and learn the characteristics of the input data, 30 epochs were selected. Convolutional, stacking, and linked layers are among the layers that make up the CNN model. A collection of adaptive filters is used by the convolutional layers to extract features from the input data. These criteria were selected in accordance with actual findings and earlier studies conducted in the area. The evaluation of AlexNet, VGG-19, VGG-16, Dense Net 201, ResNet-50, and Inception V3 models on the same dataset [13] shows that VGG-16 gives the minimum accuracy of 91.38 %, while the modified InceptionV3 model achieved the highest accuracy of 98.89 %. There is a minor difference in the accuracies attained VGG-19, Dense Net-201, and ResNet-50 shown in Fig. 11.

**Table 3**
Optimal values of model parameters.

| Parameter | Pre-set optimal value |
|---|---|
| Momentum | 0.9 |
| Learning rate drop factor | 0.1 |
| Ridge regularized | 0.0001 |
| Learning rate drop period | 10 |

Accordingly, the authors integrated the modified Inception V3 model with the Auto Contrast Enhancer, Tumor Detector and Classifier for the classification of tumors into benign and malignant classes. The confusion matrix obtained for the modified Inception V3 model shows that it wrongly classified a Benign tumor sample as Malignant and four Malignant tumour samples as benign tumors. The low number of misclassifications proves the reliability of the model. Furthermore, the modified Inception V3 model uses the finest number of network layers to minimize the time required for feature abstraction and maximize the accuracy and sensitivity of benign tumors (sensitivityB) and malignant tumors (sensitivity$_M$). Results reveal a sensitivity$_B$ of 96.89 %, sensitivity$_M$ of 97.45 % and accuracy of 98.89 % for the Inception V3 model, as shown in Fig. 12. The high values of sensitivity for both benign and malignant tumors and high accuracy prove the importance of integrating the Inception V3 model into the proposed Auto Contrast Enhancer, Tumor Detector and Classifier system in this research. The proposed system effectively handles the class imbalance problem by

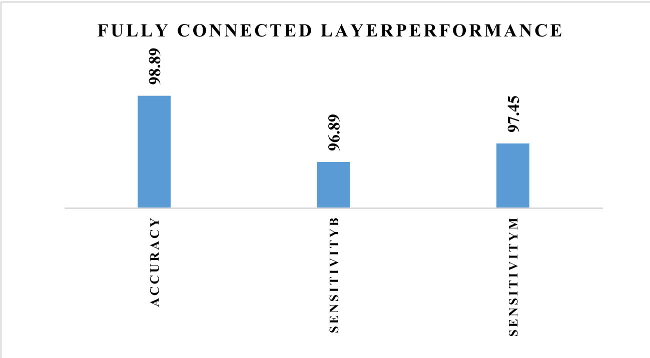


**Fig. 12.** Experimental results of Inception.

thresholding with prior probabilities, which is mainly incorporated in ODWTCHE technique. Entropy and peak signal-to-noise ratio (PSNR) are two often used measurement methods in image quality assessment. These two measurement parameters, particularly in MRI images, are used to assess the quality of imperceptibility. Based on the findings of testing and analysis, this study shows that better-quality images for tumor identification and classification are more accurate than raw images.

Further, the performance of the suggested system was examined by comparing it with the relevant studies in the literature [9–11], as displayed in Fig. 13. Rehman et al. [9] adopted the AlexNet architecture and attained the greatest accuracy of 97.39 %. Swati et al. [10] employed a transfer learning approach termed block-wise fine-tuning and attained an average accuracy of 94.82 %. Similar to this, Deepak and Ameer [11] reported a classification accuracy of 97.1 % using a pre-trained GoogLeNet model to extract the features from MRI brain pictures. The modified Inception V3 model performs better than the models used in the existing works, as shown by the comparison shown in Fig. 13. Along with the parameters and reasoning behind parameter selections, a thorough explanation is provided for the number of layers in the CNN, the kind of layers used (such as convolutional, pooling, and fully connected), and the number of filters or nodes in each layer. The CNN's parameter selection is based on a specific number of epochs. The measures that are used to evaluate the performance of the CNN include area under the ROC curve, F1 score, accuracy, precision, and recall.

In order to evaluate transfer learning, more research was done using the publicly accessible CE-MRI dataset [13]. The number of layers, network weights, and hyperparameters—namely, momentum, learning rate drop factor, L2 regularization, and learning rate drop period—in the suggested system were adjusted. Six pre-trained CNN models—AlexNet, VGG-16, VGG-19, Dense Net, ResNet-50, and Inception V3—were evaluated further for their classification performance. On the CE-MRI dataset, Inception V3 fared better than the other models, according to the comparison shown in Fig. 14.

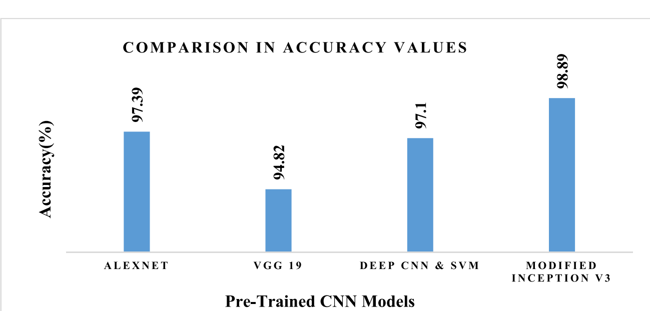


**Fig. 13.** Comparison of proposed two-phase CNN based brain tumor classification systemwith the state-of-the-a t methods.

To host the data and code on the Figshare database, which is a well-known and extensively used open-access repository that makes it simple to share and identify research findings. The decision to use Figshare is consistent with arXiv and arXivLabs' shared goals of community and openness. With respect to the parameter selections, 30 epochs were chosen. One hyperparameter that regulates how many times the training data is processed through the model during training is the number of epochs. A higher iteration count may result in improved model performance. It should be emphasized that the performance of machine learning models can be considerably impacted by the selection of hyperparameters, such as the number of epochs. In order to discover the best collection of hyperparameters for a particular problem, it is consequently commonly advisable to undertake a systematic search across a variety of hyperparameter values. This decision was probably made in an effort to find a balance between the computational resources at hand and the demand for good model performance.

## 5. Conclusions and future scope

This research proposes an automatic, intelligent, hybrid system termed Auto Contrast Enhancer, Tumor Detector and Classifier for detecting and classifying brain tumors. The system utilizes the potential of transfer learning to obtain the optimal performance of the deep learning-based system even when a small dataset is available for training. In the first phase, the system employs ODTWCHE for pre-processing low-contrast MRI images, followed by brain tumor detection. In the second phase, the system utilizes the Inception V3 pre-trained model to automatically extract all high and low-level features from brain MRI images for brain tumor classification. The suggested system is efficient in accurately identifying and classifying the tumor because it integrates contrast enhancement techniques with deep transfer learning for brain tumor diagnosis and classification. It is a robust structure for automated identification and classification of brain tumors. The proposed system was tested on the openly accessible Fig share database [13] and achieved the highest accuracy of 98.89 % compared to existing systems in the literature [11–14], such as AlexNet [11], VGG-16 [12], VGG-19 [12], Dense Net [14], and ResNet-50 [15]. MRI images of varying contrasts were further used to assess the proposed system's performance. On the basis of simulation results, the authors claim that the performance of the system does not degrade with the change in contrast and brightness of the MRI image, proving the system's robustness. The Proposed work can illustrate the high accuracy of its models by offering a comparison table or graph displaying the accuracy rates of the suggested models alongside other existing models. It can include a part describing the numerous tests and validations carried out to make sure the models function properly under various circumstances and with diverse datasets in order to highlight the models' robustness. If the study provides a thorough explanation of how previously trained models were adjusted for the particular task at hand, it can highlight the application of transfer learning. Figures showing the transfer learning process can go along with this. The advantages of transfer learning, such as shortened training times and enhanced output.

Moreover, the proposed system can be hosted on the Cloud and may become a useful technological assistant for health experts when screening tumors at an early stage. The proposed system's limitations include its tendency to base assessments and predictions on training data and its potential inability to adapt its knowledge to novel circumstances. It is challenging to recognize and resolve problems like bias and lack of robustness. Increasing the transparency of AI systems using methods like explainable AI can aid in resolving these issues. Although there is room for improvement in the proposed system, there may not be any direction or assistance in putting the improvements into practice. It could be necessary to set up accountability and follow-up procedures to make sure the person acts in future work.

Although this work explored different architectures related to deep transfer learning and CNN, there is huge scope to optimize the system's

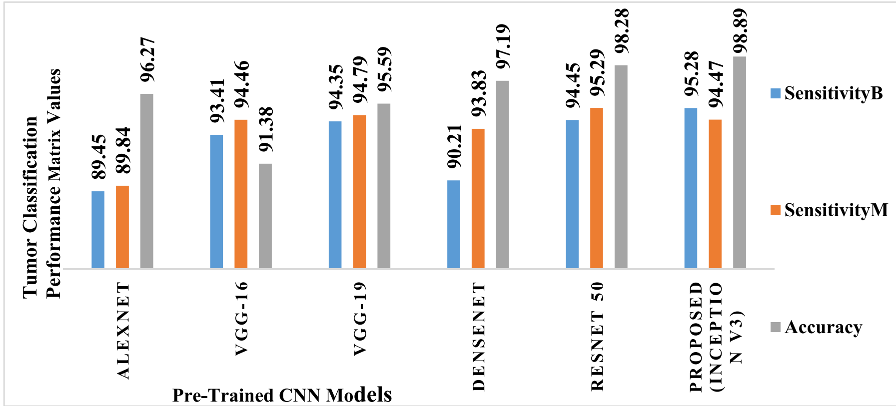


**Fig. 14.** Comparative results of different pre-trained CNN models on CE-MRI datasets.

performance and reduce the response time for quick and mass screening of brain tumor from different modalities.

## CRediT authorship contribution statement

**Monika Agarwal:** Writing – original draft. **Geeta Rani:** Methodology. **Ambeshwar Kumar:** Conceptualization. **Pradeep Kumar K:** Supervision. **R. Manikandan:** Investigation. **Amir H. Gandomi:** Writing – review & editing.

## Declaration of competing interest

There is no Conflict of Interest.

## Data availability

Data will be made available on request.

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