An Optimized Deep Learning Model with Transfer Learning-Based Feature Extraction for Brain Tumor Classification

Dr. G. Suresh

Assistant Professor, Department of Computer Science, Government Arts College for Women, Salem – 636 008, Tamil Nadu, India, Email: suresh2023phd@gmail.com

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ABSTRACT
The early and accurate detection of brain tumors is critical for effective treatment and patient survival. In this paper, we propose a novel approach for brain tumor detection that integrates various preprocessing and deep learning techniques to enhance diagnostic accuracy. The method begins by applying a Median Filter (MF) for noise reduction, ensuring the removal of image artifacts while preserving important structural details. Contrast Limited Adaptive Histogram Equalization (CLAHE) is then used to enhance contrast, improving the visibility of critical features within brain CT images. For feature extraction, we employ EfficientNet, a state-of-the-art convolutional neural network known for its balance between performance and efficiency. The extracted features are passed through a custom deep learning model designed for tumor classification. The ADAM optimizer is used to fine-tune the hyperparameters, achieving optimal training performance. Model evaluation is performed using accuracy, precision, recall, and F1-score metrics, providing a comprehensive assessment of the model's effectiveness. Experimental results demonstrate that the proposed system achieves high accuracy in detecting brain tumors, showcasing its potential as a reliable tool for clinical diagnosis.

Keywords: Brain tumor, Median filter, CLAHE, Efficient Net, Deep Learning, ADAM Optimizer, CT images

1. INTRODUCTION

Brain tumors pose a significant challenge in the field of medical diagnosis due to their complexity, variability, and serious implications for patient health. Early and accurate detection of brain tumors is critical for determining the best course of treatment and improving survival rates. Computed Tomography (CT) imaging, a widely used and non-invasive diagnostic tool, plays a vital role in identifying abnormal growths in the brain. However, the manual analysis of CT scans is both time-consuming and prone to human error, requiring highly skilled radiologists for precise interpretation. These challenges have led to increasing interest in automated systems that can assist or replace manual methods in brain tumor detection.In recent years, deep learning has emerged as a powerful tool for medical image analysis, including the detection and classification of brain tumors. Convolutional Neural Networks (CNNs), a type of deep learning architecture, have shown remarkable success in extracting features and recognizing patterns in medical images. However, the performance of these models depends heavily on the quality of input images and the effectiveness of feature extraction. Proper preprocessing and advanced feature extraction techniques are crucial to improve the model's ability to detect brain tumors accurately.

This paper proposes an optimized deep learning model for brain tumor detection using CT images. The process begins with noise reduction, employing a median filter to remove artifacts commonly present in CT scans while preserving key structural details. Noise, such as speckles or other unwanted variations, can obscure critical features of the brain and tumors, reducing the reliability of the detection process. By applying a median filter, we can effectively reduce this noise and enhance the image quality for subsequent analysis.Next, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance image contrast. CT images, particularly those involving brain tumors, often suffer from poor contrast, making it difficult to distinguish between healthy tissue and tumors. CLAHE improves local contrast adaptively, enhancing subtle details and ensuring that important features, such as the shape, texture, and boundaries of tumors, are more clearly visible in the images.For feature extraction, we utilize EfficientNet, a state-of-the-art Convolutional Neural Network architecture that leverages transfer learning. EfficientNet is designed for high performance and computational efficiency, making it ideal for medical applications where large datasets and high accuracy are needed. By using transfer learning, we take advantage of pre-trained weights from large-scale image classification tasks, allowing the model to extract high-level features from CT images that are critical for brain tumor detection.

To further improve the performance of the deep learning model, we use the ADAM optimizer to fine-tune the model's hyperparameters during training. The ADAM optimizer, which combines the advantages of both the Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp), is particularly suited for handling sparse gradients, a common issue in medical imaging datasets. This optimization method allows for faster convergence and better performance by dynamically adjusting learning rates during training.The performance of the proposed model is evaluated using a comprehensive set of metrics, including accuracy, precision, recall, and F1-score. These metrics provide insights into the model's capability to accurately classify CT images and detect brain tumors. Our results demonstrate that the proposed method achieves superior performance compared to existing approaches, with high detection accuracy and strong performance across multiple evaluation metrics.

The structure of this paper is as follows: Section 2 discusses related work in brain tumor detection and deep learning techniques. Section 3 details the methodology, including preprocessing with median filtering, contrast enhancement with CLAHE, and feature extraction using EfficientNet. Section 4 presents the experimental setup and discusses the results and findings. Finally, Section 5 concludes the study and outlines potential directions for future research.

2. RELATED WORKS

JavariaAmin et. al. [1] presents a deep segmentation approach that utilizes an encoder-decoder architecture for brain tumor detection.The encoder employs convolutional neural networks (CNNs) to extract spatial information from MRI images.Transfer learning is highlighted as a promising strategy to leverage pre-trained models for improved segmentation performance.Jaeyong Kang et. al. [2]proposes a new method for brain tumor classification that combines deep learning and machine learning techniques. This framework utilizes an ensemble of deep features extracted from brain MRI images, which enhances the classification accuracy compared to traditional methods. The authors identify and select the top three deep features that perform well across various machine learning classifiers. These features are then concatenated to form an ensemble, which is fed into multiple classifiers.A.T. Omurkanova [3] outlines several methods employed in developing a new diagnostic model for brain tumors, focusing on feature extraction and optimization techniques.The proposed model incorporates CNNs, which are powerful tools for image analysis.To improve the model's accuracy, the authors apply optimization algorithms.

R. Premalathaet. al. [4]proposes a novel approach using neutrosophic logic for image fusion. This method effectively combines information from multiple MR images, improving the overall quality and reliability of the resulting images. Neutrosophic logic allows for the representation of uncertainty and indeterminacy, which is crucial in medical imaging.The proposed method demonstrates a marked improvement in image quality compared to traditional fusion techniques. Shailendra Kumar Mishra et. al. [5]presents several significant contributions to the field of medical imaging and brain tumor classification.The paper utilizes EfficientNet, a pre-trained Convolutional Neural Network (CNN) model, to extract deep features from brain MRI images. This model is known for its efficiency in scaling all dimensions uniformly, which enhances the classification performance. G. Lavanyaet. al. [6]proposes a hybrid model that combines the EfficientNet deep learning architecture with the Fuzzy C Means clustering algorithm. This integration aims to enhance the accuracy of brain tumor detection from MRI images, addressing the limitations of existing models that do not incorporate segmentation algorithms. By utilizing deep learning techniques, the proposed model facilitates the early detection of brain tumors, which is crucial for improving patient outcomes and potentially reducing mortality rates.

Adam P. Balcerzak [7] delves into the challenges associated with the normalization of Magnetic Resonance (MR) images. It highlights how different normalization techniques can impact the quality of the images and subsequently affect the performance of classification models used for brain tumor detection. The authors provide empirical evidence showing that the choice of normalization technique can lead to substantial differences in classification performance, which is crucial for clinical applications. Francisco Javier Díaz-Pernaset. al. [8]proposes a novel MC-CNN architecture specifically designed for the classification and segmentation of brain tumors. This architecture allows the model to capture features at multiple scales, improving its ability to analyze complex medical images.Anichur Rahman et. al. [9]proposes two deep learning models specifically designed for the detection and classification of brain tumors. These models are capable of identifying both binary and multiclass tumors, which enhances the diagnostic capabilities of radiologists. S. V. Srinivasanet. al. [10]proposes a new automated detection and classification method for brain tumors, which includes multiple phases such as pre-processing, segmentation, feature extraction, and classification of MRI images. This comprehensive approach aims to enhance the accuracy of tumor identification.

3. PROPOSED METHODOLOGY

In this study, a novel deep learning technique for the brain tumor detection using CT images was introduced. The proposed approach involves different stages of operations such as MF based pre-processing, CLAHE based contrast enhancement, EfficientNet based feature extraction, and DL model based tumor classification. The block diagram for the proposed approach is shown in Figure 1.

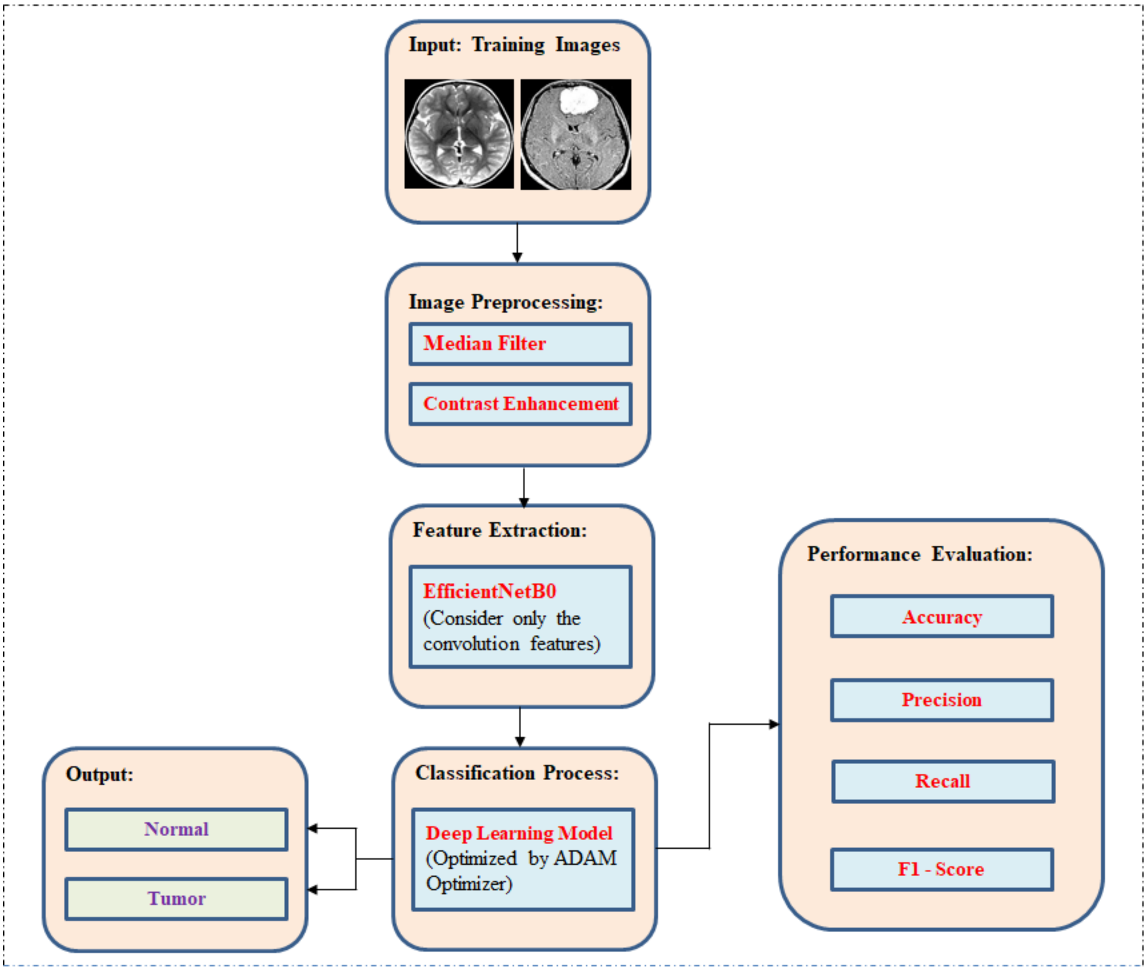


Figure 1: Block diagram of proposed approach

3.1. Image Pre-processing

The proposed model primarily uses MF-based noise reduction and CLAHE-based contrast enhancement. In medical imaging, including CT scans, noise is a common issue that can degrade the quality of images, making it difficult to detect and analyze critical features, such as brain tumors. Noise may originate from several factors, including patient movement, the imaging environment, or hardware limitations. For accurate diagnosis, it is essential to reduce or remove noise while preserving important structures within the image.

A Median Filter is a widely used non-linear filtering technique, especially effective in reducing impulse noise while preserving the edges and details of the image. Unlike linear filters that blur edges, the median filter replaces each pixel's value with the median value of the neighboring pixels within a defined window. This operation smooths out noisy pixels without affecting the image's sharpness, which is particularly important for medical imaging where the boundaries between healthy tissue and tumors must remain intact.

Let the original noisy CT image be denoted by I_{noisy} , and the noise-reduced image by $I_{filtered}$. The relation between the two after applying the median filter is:

$$I_{filtered}\,(x,y) = median(W_{m*n}(I_{noisy}\,(x,y))) \qquad (1)$$

This filtered image serves as the input to subsequent stages in the detection pipeline, such as contrast enhancement and feature extraction.

Adaptive Histogram Equalization (AHE) is a sort of approach that includes CLAHE. Through the use of the clip limit and amount of tiles parameters, the CLAHE addresses the over amplification issues of standard

AHE. The image is divided into MxN local tiles via CLAHE.The histogram has been produced separately for each tile. The histogram on a computer first determines the average number of pixels in each zone as shown below.

$$N_A = \frac{N_X \times N_Y}{N_G} \tag{2}$$

Here, N_a represents the average count of pixels, N_x indicates the count of pixels from the X dimensional and N_Y shows the count of pixels from Y dimensional and N_G shows the amount of gray levels. Next, determine the clip limit from Eq. (3) for clipping the histogram.

$$N_{CL} = N_A \times N_{NCL} \tag{3}$$

In the following, N_{CL} denotes the clip limit and N_{NCL} shows the normalization clip limit amongst zero and one. Then, for all the tiles, the clip limit has been employed for height of histogram as follows.

$$H_i = \begin{cases} N_{CL} & if N_i \geq N_{CL} \\ N_i & else \end{cases} \quad i = 1,2,..,1-1 \tag{4}$$

Let, H_i be the height of histogram of i-$t\hbar$ tiles, N_i shows the histogram of i-$t\hbar$ tiles and L indicates the amount of gray levels. The overall amount of clipped pixels is calculated as follows.

$$N_c = (N_X \times N_Y) - \sum_{i=0}^{L-1} H_i \tag{5}$$

Where, N_C indicates the count of clipped pixels. Afterward computingN_C, redistribute the clipped pixel. The pixel is redistributed uniformly/non-uniformly. The number of pixels that are redistributed is calculated as follows.

$$N_R = \frac{N_C}{L} \tag{6}$$

Where, N_R denotes the count of pixels thatredistribute. Afterward, the clipped histogram was normalized as follows.

$$H_i = \begin{cases} N_{CL} & if N_i + N_R \geq N_{CL} \\ N_i + N_R & else \end{cases} \quad i = 1,2,..,1-1 \tag{7}$$

Eqs. (5) and (6) calculate the number of un-distributed pixels.Each pixel is distributed evenly by repeating Eq. (7).Finally, the context region's cumulative histogram is constructed as follows.

$$C_i = \frac{1}{(N_X \times N_Y)} \sum_{j=0}^{i} H_j \tag{8}$$

After the calculation is complete, the context region's histogram was found to match to a uniform, Rayleigh, or exponential probability distribution, which offers a corresponding brightness and visual quality. The pixel $P(X, Y)$ with value of s and 4center points belongs to the neighboring tiles as R_1, R_2, R_3,and R_4. These 4 context regions are used to determine the weight sums. The following expression achieves the new value of$s$, which can be represented bys', by combining the tiles and using bilinear interpolation to remove artefacts from the individual tiles.

$$s^{'} = (1-y)((1-X) \times R_1(s) + X \times R_2(s))$$
$$+y((1-X) \times R_3(s) + X \times R_4(s))) \tag{9}$$

Finally, the improved image is achieved.

3.2. Feature Extraction

In order to produce meaningful feature vectors at this point, the reported proposed approach used an EfficientNet-based feature extractor. The EfficientNetB0 network utilizes the recombination coefficient to automatically modify the model's resolution, depth, and width and offers the advantages of high recognition accuracy and compact parameters [11]. The greyscale brain image with a resolution of 224x224 pixels that is the input of EfficientNetB0 has 2 convolution layers, 16 Mobile Inverted Bottleneck Convolution (MBConv) modules, 1 classification layer, and 1 global average pooling layer. By using a drop connect rather than a traditional dropout, MBConv significantly reduces the likelihood of the model overfitting.

EfficientNet-B0 scaling tries to extend the resolution (H_i, W_i), length (L_i), and width (C_i) of the network without changing F_j predetermined in the baseline network, and restrict the uniform scaling of each layer at a constant ratio to decrease the design space. To obtain the maximum model accuracy under any given resource constraints, the target is expressed through the following optimization problem:

$$\max_{d,w,r} Accuracy(N(d,w,r))$$
$$s.t. N(d,w,r) = \bigodot_{i=1,\dots s} \hat{F}_i^{d \cdot \hat{L}_i} \left(X_{\langle r \cdot \widehat{H_i}, r \cdot \widehat{W_i} w \cdot \hat{C}_i \rangle} \right) \tag{10}$$

Memory $(N) \leq tar_$memory

Flops $(N) \leq tar\_flops$

In Eq. (10),w, and r denotes the depth, width, and resolution coefficients of the scaling network, correspondingly. Furthermore, $\hat{F}_i, \widehat{L_i}$, and $\hat{C}_i$ refers to the predetermined network architecture, predetermined layers, and predetermined channels, correspondingly and $\widehat{H_i}$and $\widehat{W_i}$denotes predetermined resolutions. Furthermore, $< \hat{H}_i, \hat{w}_i, \hat{C}_j >$ signifies the shape of input tensor X corresponding to layer i, Memory (N) and Flops (N) are the parameters and floating point of the network operation, correspondingly. Lastly, tar-flops and tar-memory are floating points of the operation and the threshold of the parameter, correspondingly.

In EfficientNet-B0, the compound coefficient φ is used for uniformly scaling the resolution, depth, and width of the network to obtain better accuracy and efficiency and balance the relationships between the three dimensions in the following:

$$d = \alpha^{\phi}, w = \beta^{\phi}, r = \gamma^{\phi}$$
$$s.t. \quad \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \qquad (11)$$
$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$$

Let ϕ be a user defined coefficient that is controlled on the basis of available resources. Instinctively, β and γ represent the resource control coefficient that determines how to assign the resource to the resolution, depth, and width, correspondingly.

3.3. Image Classification

For tumor detection and classification, an efficient deep learning model is proposed. Deep learning and artificial intelligence methods that mimic how people learn are related to machine learning methods. Deep learning is a crucial part of data science, which also encompasses statistics and predictive modelling. DL model is used to classify and detect images due to its high degree of accuracy. The table 1 shows the architecture of proposed deep learning model.

Table 1: Proposed Deep Learning Model: Architecture

Stage	Layer	Output Shape	Filters	Parameters
1	Rescaling	254 x 254		
2	Conv2D	254 x 254	16	448
3	MaxPooling2D	112 x 112	16	0
4	Conv2D	112 x 112	32	4640
5	MaxPooling2D	56 x 56	32	0
6	Conv2D	56 x 56	64	18496
7	MaxPooling2D	56 x 56	64	0
8	Flatten	50176		0
9	Dense	128		6422656
10	Dense	2		258

Total params: 6,446,498
Trainable params: 6,446,498
Non-trainable params: 0

On top of the model a new Rescaling layer is added to rescale the input images into fixed size. To rescale an input in the [0, 255] range to be in the [0, 1] range, would pass scale=1./255. The rescaling is applied both during training and inference. Inputs can be of integer or floating point dtype, and by default the layer will output floats.

A tensor of outputs is produced by the Conv2D layer by creating a convolution kernel that is convolved with the layer input.A conv2D layer's filter or kernel applies an element wise multiplication to the 2D input data by "sliding" over it. It will therefore combine the outcomes into a single output pixel.

A Pooling layer is frequently added after a Convolutional layer. The ultimate goal of this layer is to lower computationalexpenses by reducing the size of the convolved feature map.The dimension of the output matrix can be computed using the following formula after pooling.

$$\left(\frac{n_h - f}{s} + 1\right) \times \left(\frac{n_w - f}{s} + 1\right) \times n_c \qquad (12)$$

In Eq. (12), n_h denotes feature map's height, $n_w$indicates feature map's width, $n_c$shows channel count in the feature map, f denotes filter size and s indicates length of stride.

Each neuron in the dense layer, which is a straightforward layer of neurons, receives input from every neuron in the preceding layer. Based on the results of convolutional layers, animage is classified using a dense layer. The output depends on the functioning of a single neuron. Suchneurons are distributed throughout a layer.

The Adam approach is used to calculate the adaptive learning value when the parameters are used to train the DNN model's parameters.With little memory available for stochastic optimization, it is a practical and effective solution for firstorder gradients.In this situation, the newly given model has been used to address ML problems with enormous datasets, higher-dimensional parameter spaces, and approximations using 1st and 2nd-order moments. The first momentum has been attained by,

$$m_i = \beta_1 m_{i-1} + (1 - \beta_1)\frac{\partial C}{\partial w}. \quad (13)$$

The 2nd momentum is expressed by,

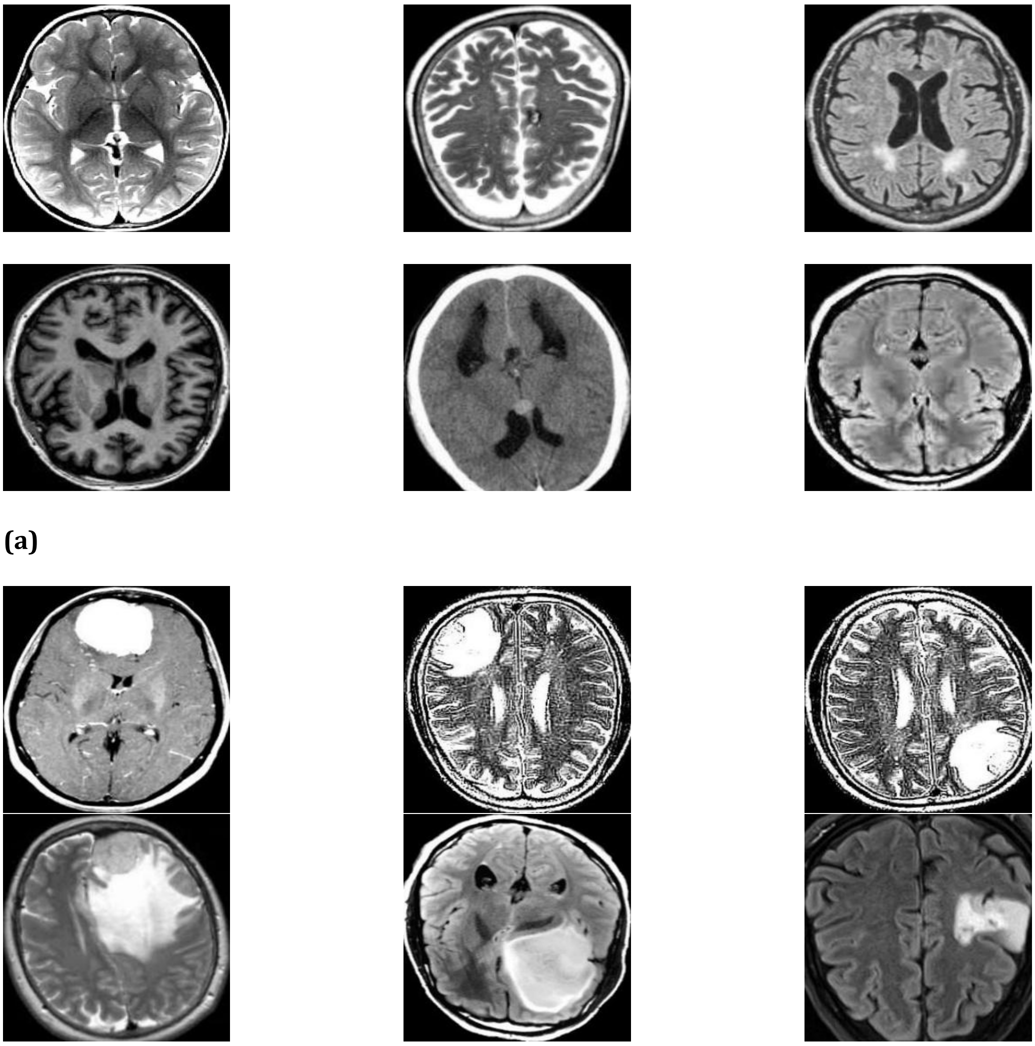
$$v_i = \beta_2 v_{i-1} + (1 - \beta_2)\left(\frac{\partial C}{\partial w}\right)^2. \quad (14)$$

$$w_{i+1} = w_i - \eta \frac{\hat{m}_i}{\sqrt{\hat{v}_i + \epsilon}}, \quad (15)$$

where $\hat{m}_i = m_i/(1 - \beta_1)$ and $\hat{v}_i = v_i/(1 - \beta_2)$.Adam limits the processing cost, demands for lower memory space, and invariant for diagonal rescaling.

4. Performance Validation

The presented model is simulated using Python tool. To validate the performance of the proposed method, the UCSD-A14H dataset is used [12] which consists of 170Normal images and 230Tumor images. From the database, 80% of the data is consumed for the training phase, and 20% of the data is consumed for the testing phase. Figure 2 presents some sample original images.



(b)

Figure 2: Sample Images a) Normal b) Tumor

Table 2 depicts the detailed description of dataset.

Table 2: Dataset details

Class Names	No. of Samples
Normal	170
Tumor	230

Figure 3 presents the confusion matrices generated by the proposed model for the categorization of brain normal and tumor images in the training and testing sets.

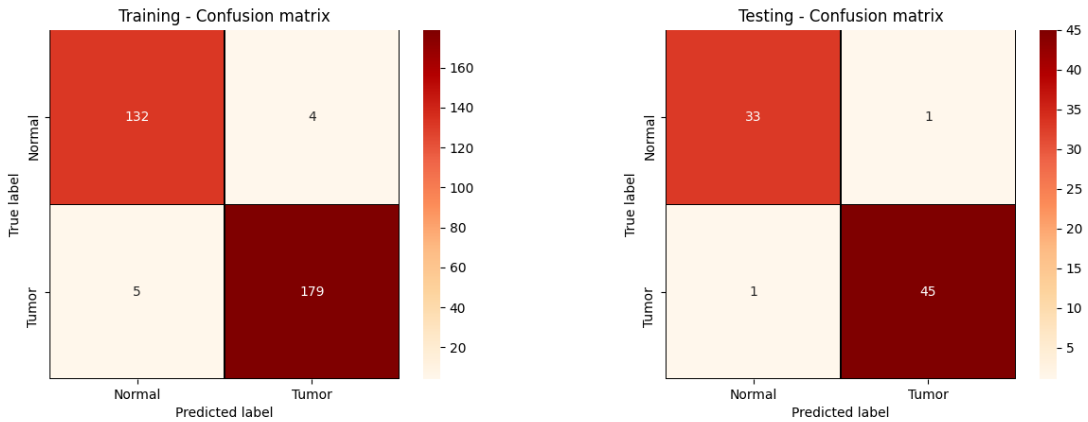


Figure 3: Confusion matrix of proposed model for training and testing sets

Table 3: Result analysis of proposed technique for training and testing sets

Metrics	Training Set	Testing Set
Accuracy	97.12	98.50
Precision	97.05	97.05
Recall	96.35	97.05
F1-Score	96.70	96.60

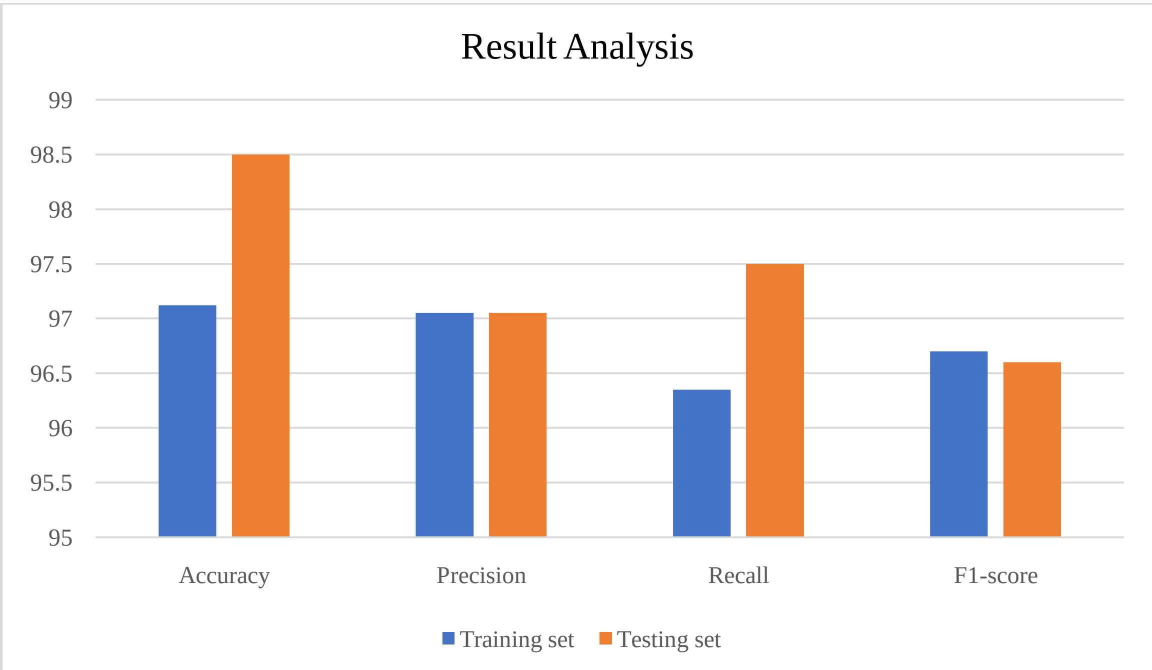


Figure 4: Graphical representation of metrics achieved

Table 3 and figure 4 shows the result analysis of different metrics achieved for training and testing set.
A comparative analysis of the proposed method against existing state-of-the-art models is presented in Table 4 and Figure 5, highlighting the improved performance of our approach. The experimental results show that the Recurrent Neural Network (RNN), Deep Belief Neural Network (DBNN), and Long Short Term Memory (LSTM) models achieved lower accuracy rates of 96.38%, 92.81%, and 89.94%, respectively. In contrast, the proposed model demonstrated superior performance, achieving an accuracy of 98.50%. The detailed results and analysis clearly indicate that our proposed model outperformed the other models.

Table 4: Accuracy analysis of proposed approach with existing algorithms

Methods	**Accuracy (%)**
Proposed	98.50
RNN	96.38
DBNN	92.81
LSTM	89.94

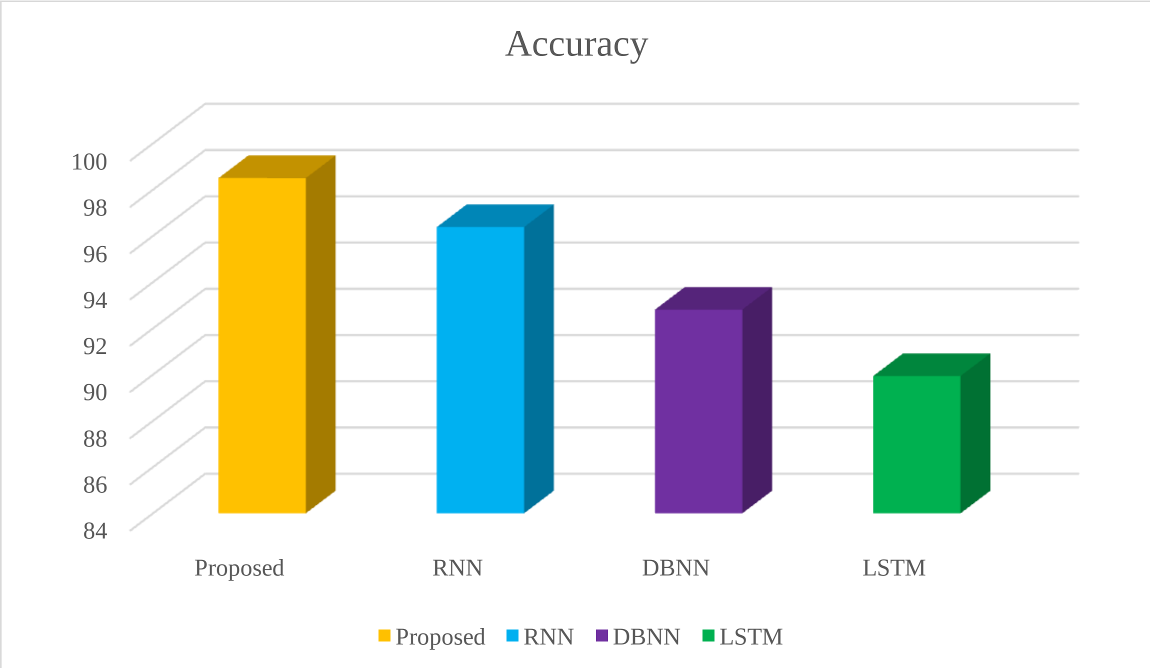


Figure 5: Comparative analysis of proposed approach with existing algorithms

5. CONCLUSION AND FUTURE WORK

In this study, we have proposed a comprehensive deep learning-based approach for brain tumor detection using CT images. The method combines several key techniques, including median filtering for noise reduction, Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement, EfficientNet for feature extraction via transfer learning, and a custom deep learning model optimized using the ADAM optimizer. This integrated framework was designed to improve the accuracy, robustness, and reliability of tumor detection in CT images, addressing many of the limitations faced by traditional diagnostic approaches. The proposed model was thoroughly evaluated using standard performance metrics, including accuracy, precision, recall, and F1-score. Comparative analysis with state-of-the-art models such as Recurrent Neural Networks (RNN), Deep Belief Neural Networks (DBNN), and Long Short-Term Memory (LSTM) networks demonstrated the superiority of our approach. While these models achieved respectable accuracy levels of 96.38%, 92.81%, and 89.94%, respectively, our proposed method significantly outperformed them, achieving an accuracy of 98.50%.
This notable improvement highlights the effectiveness of our model's design, particularly in handling complex medical image data and capturing fine-grained features of brain tumors. Future work could involve the extension of this framework to other types of medical imaging, as well as further optimization to enhance generalization across diverse datasets. Additionally, the integration of this method into clinical workflows, potentially in real-time tumor detection systems, could provide substantial benefits for early diagnosis and treatment planning.

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