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A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet

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ABSTRACT A brain tumor is a disorder caused by the growth of abnormal brain cells. The survival rate of a patient affected with a tumor is difficult to determine because they are infrequent and appear in various forms. These tumors can be identified through Magnetic Resonance (MRI) Images, which plays an essential role in determining the tumor site; however, manual detection is a time-consuming and challenging procedure that can cause some errors in results. The adoption of computer-assisted approaches is essential to help in overcoming these constraints. With the advancement of artificial intelligence, deep learning (DL) models are being used in medical imaging to diagnose brain tumors using MR images. In this study, a deep convolutional neural network (CNN) EfficientNet-B0 base model is fine-tuned with our proposed layers to efficiently classify and detect brain tumor images. The image enhancement techniques are used by applying various filters to enhance the quality of the images. Data augmentation methods are applied to increase the data samples for better training of our proposed model. The results show that the proposed fine-tuned state-of-the-art EfficientNet-B0 outperforms other CNN models by achieving the highest classification accuracy, precision, recall, and area under curve values surpassing other state-of-the-art models, with an overall accuracy of 98.87% in terms of classification and detection. Other DL algorithms such as VGG16, InceptionV3, Xception, ResNet50, and InceptionResNetV2 are used for comparative analysis.

INDEX TERMS Brain tumor, deep learning, convolution neural networks (CNN), transfer learning, MRI, detection.

I. INTRODUCTION

A brain tumor is a disorder caused by the development of abnormal cells or tissues in the brain [1]. Cells generally reproduce and die in a regular sequence, with each new cell replacing the previous one. However, some cells become abnormal and continue to grow, causing severe damage to the brain functions, and often leading to death. A minimum of 120 multiple types of brain tumors and the central nervous system (CNS) exist. According to the American Cancer Society, 18,600 adults and 3,460 children under 15 will die due to brain and CNS tumors in 2021. The 5-year survival rate for the patients having brain tumors is only 36%, and the 10-year survival rate is 31% [2]. Furthermore, National Cancer Institute reported 86,010 multiple cases of brain cancer and CNS cancers diagnosed in the United States in 2019. It was predicted that roughly 0.7 million people in the United States suffer from brain tumors. A total of 0.86 million cases were identified, of which 60,800 patients had benign tumors, and 26,170 patients had malignant tumors [3]. World Health Organization reported that 9.6 million people worldwide are estimated to have been diagnosed with cancer in 2018 [4].

One of the most significant aspects of saving a patient's life is early brain tumor diagnosis. The proper examination of

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brain tumor images is vital in evaluating a patient's condition. The conventional method of detecting brain tumors includes a doctor or radiologist examining magnetic resonance (MR) images for anomalies and making decisions. However, it is strongly dependent on a doctor's medical expertise; disparities in experience levels and nature of images create extra complexity for diagnosing with naked human eyes [5]. It is challenging for a doctor to interpret these images in a limited period since they contain several abnormalities or noisy data. As the volume of information increases, assessing a massive amount of information gets even more challenging. The manual detection of a brain tumor becomes more time-consuming and costly. Therefore, an automatic computer-aided diagnostic (CAD) system is required to assist doctors and radiologists in the timely detection of these deadly tumors to save precious human lives.

Artificial intelligence (AI) is a field of computer science that aims to give computers human-like intelligence, allowing them to learn, think, and resolve issues when confronted with various information. AI plays an essential role in identifying and diagnosing brain tumors. The discipline of brain tumor surgery is an excellent choice for additional AI integration due to its complicated and elaborate processes. Multiple attempts have been made to establish a highly accurate and reliable approach for brain tumor classification. However, the wide range of shape, texture, and contrast changes across and among individuals remains a difficult challenge to solve. Machine learning (ML) and deep learning (DL), subsets of AI, have recently revolutionized neurosurgical procedures. They consist of data preprocessing, feature extraction, feature selection, feature reduction, and classification. According to the study [6] because of AI, neurosurgeons can leave the operating room more confident than ever in terms of their patient's brain tumor diagnosis.

Deep learning, particularly neural networks, gains substantial importance when it obtains promising results. Convolutional neural networks (CNNs) are remarkable for learning features and providing unlimited precision. Many deep learning applications have been developed, including pattern categorization, object detection, voice recognition, and other decision-making tasks, [7], [8]. In previous studies, traditional ML algorithms such as support vector machines (SVMs), k-nearest neighbor (k-NN), decision trees, and Naive Bayes and DL algorithms, such as custom CNNs, VGGNets [9], GoogleNet [10], and ResNets [11], approaches are used to help the healthcare community diagnose such malicious diseases. Although researchers have made various attempts to detect tumors from MRI scans, many deficiencies exist (i.e., low accuracy, big and slow models, and high computational costs). Additionally, the more extensive data always remains a challenge in the healthcare domain because researchers cannot openly share medical information due to the privacy concerns of their patients. Furthermore, existing approaches have lower precision and recall levels, resulting in low efficiency and requiring more time for image classification, which could delay the patient's treatment [12].

Deep learning has recently been used in studies to boost the effectiveness of computer-aided medical diagnostics in brain cancer investigation. They play an essential role in the healthcare profession and act as valuable tools in various vital disorders, including brain disease diagnosis and skin cancer image analysis [13], [14]. DL methods based on transfer learning and fine-tuning are preferred and widely used for the classification of Brain tumors. The motivation of this research is to conduct extensive experimentation using deep convolutional neural networks, transfer learning, and fine-tuning to automate the process of brain tumor classification and detection. The primary contributions of our proposed study are:

- A new automated method based on the state-of-the-art EffcientNet-B0 model is fine-tuned with our recommended layers, which can replace conventional invasive brain tumor classification and enhance overall classification accuracy.
- An initial three-step image preprocessing strategy is employed to enhance the low visual quality of the MRI images.
- The data augmentation strategy is utilized to generate better outcomes on small datasets, and the effect of over-fitting phenomena on classification is studied.
- A comparative analysis is conducted regarding the accuracy, weight sizes, and parameters between our proposed model and other state-of-the-art deep CNNs models used in this study. The proposed model outperformed the other CNNs in every aspect.

The remainder of the paper is divided and organized as follows: Section 2 discusses a literature review, Section 3 presents the proposed methodology, Section 4 provides the implementation details, Section 5 represents the experimental results of the proposed techniques and a comparison with other recent state-of-the-art methods. Furthermore section 6 provides the conclusion and the future study.

II. LITERATURE REVIEW

This section reviews several related studies that employ machine learning and deep learning approaches to detect and classify infectious brain tumors and standard images. Abd-Ellah *et al.* [15] conducted a detailed research study of several diagnostic methodologies for brain MRI images. The authors also analyzed classical machine learning and deep learning techniques in terms of limitations and performance metrics. In this study [16] the authors presented several strategies for detecting brain cancers from MR images. For deeper segmentation, their study was based on three-dimensional based CNNs, SVMs, and multi-class SVMs. The DL methodology produced outstanding results and a reliable brain tumor classification and segmentation approach compared to other ML classifiers.

In a different study [17] the authors proposed a deep learning neural model to extract the features of the MR images, which are provided as input to the ML classifiers (Naive Bayes, SVMs, and Multilayer perceptrons). The proposed method achieved 96% classification accuracy with SVMs as classifiers. Hossain *et al.* [18] proposed several machines and DL methods such as SVMs, K-NN, multi-layer perceptron, Naive Bayes, and random forest algorithms for brain tumor classification and segmentation. Among all these techniques, traditional SVMs achieved the highest accuracy of 92.4% in classification. They also proposed a five-layer custom CNN architecture that attained 97.2% accuracy in detecting brain tumors in MR images. Khan *et al.* [19] proposed VGG19 CNN architecture and K-means clustering for the classification and segmentation of brain tumors in MRI images. The proposed technique converts an input MR modality to slices, and then intensities are preprocessed using a statistical normalization approach. They achieved an overall accuracy of 94%.

In the study [20] the authors presented a fusion approach by using 2D and 3D MRI images; they designed a DenseNet and custom 3D CNN architectures for classification and segmentation of multi-modal images, respectively. The proposed approach showed good performance on the testing set by achieving 92% on DenseNet and 85% on customized 3D CNN models. Kang *et al.* [21] presented an approach for classifying brain tumors using ML classifiers and an ensemble of in-depth features from pre-trained deep CNN. In this approach, the authors used three different dataset sizes (small, medium, and large). An SVM classifier with a radial basis function kernel obtained the highest accuracy compared to other ML and DL classifiers. In [22] an entirely automated brain tumor classification system based on ML networks was proposed to detect high- and low glioma disease images. The authors used an extreme gradient boosting model to perform the multi-classification of brain tumors into primary, secondary, and central nervous system brain tumors by achieving 90% and 95% accuracy. The authors of [23] proposed an enhanced classification and segmentation ensemble model called ‘‘Adaptive Fuzzy Deformable Fusion’’ by merging the Fuzzy C-Means Clustering and deformable snake approach. The experimentation showed that the ensemble technique obtained better results by achieving 95% classification accuracy.

Mehrotra *et al.* [24] presented various deep learning-based pre-trained CNN techniques for distinguishing benign and malignant brain tumor images. They used different optimizers to complete the tasks, namely Adam, RMSprop, and stochastic gradient descent (SGD). Their research demonstrated that a fine-tuned AlexNet could perform exceptionally well on medical imaging tasks. Grampurohit and Shalavadi [25] developed a custom CNN architecture and VGGNet for classifying 253 brain tumor images, of which 155 were tumors, and 98 were non-tumors. They used data preprocessing and augmentation techniques for increasing variation in the data samples to reduce the overfitting of the proposed models. The customized CNN model attained an overall validation accuracy of 86%, while VGGNet exhibited the highest validation accuracy of 97% on a particular dataset. The authors of this paper [26] reviewed several image preprocessing techniques for image manipulation, which significantly improved the classification results. The authors proposed global thresholding, adaptive thresholding, Sobel filter, high-pass filter, median blur, histogram equalization, dilations, and erosions. In addition, they also presented a transfer learning-based pre-trained Resnet101 V2 model to detect the brain tumors in 3762 images. Their results showed a 95% accuracy rate. In this research [27] the authors deployed a hybrid strategy based on CNNs and a genetic algorithm (GA) to detect glioblastoma and different brain tumor types. This proposed approach employed a genetic algorithm to choose a CNN structure automatically. The authors predicted the glioma pictures of three varieties with 90.9% accuracy. This study’s classification of glioma, meningioma, and pituitary cancer was 94.2% accurate.

Majib *et al.* [28] proposed a hybrid approach, called VGG-SCnet, by combining VGGNet with a stacked classifier. In their study, a pre-trained VGG-16 architecture is fine-tuned with their suggested layers for quicker and more effective training to detect brain tumors from MRI scans automatically. Data preprocessing first identified the most prominent contours to identify the region of interest. Next, the augmentation technique was used to eliminate the class imbalance problem in the dataset. The features were extracted in the sixth layer because it provides fewer features. A stacked classifier was used to determine if an image contains tumors. Meanwhile, image preprocessing is used to construct an image of the human body’s anatomical structure, as explained in [29] and MRI images are used to locate tumor cells in a diseased human brain. In this paper [30] a method for detecting 3D MRI brain tumors is proposed, which combines multimodal information fusion with CNN. Multimodal 3D-CNNs were upgraded to obtain the properties of brain tumor lesions under various modalities. In [31], the researchers provided various categorization algorithms based on CNN architectures, including VGGNets, GoogleNet, and ResNets, each with several repetitions. ResNet-50 has a higher accuracy rate of 96.50%, followed by GoogleNet, and VGGNets achieving 93.45% and 89.33% accuracy rates. ResNet-50 produces 10% more accurate results in 10% lesser time than VGGNet and GoogleNet.

III. PROPOSED METHODOLOGY

The proposed model with multiple layers and pre-trained algorithms will be thoroughly discussed in the subsequent sections. Figure 1 depicts the stages of the brain tumor image preprocessing, augmentations, training, and evaluation. The proposed transfer learning and fine-tuning method are based on DL algorithms that use numerous hyperparameters for training and optimization. An optimizer is an algorithm that adjusts the neural network biases and learning rate. As a result, it aids in lowering total loss and improving accuracy. A loss function demonstrates how well a specific algorithm matches the given data for ML. With the help of an optimization function, the loss function gradually learns to decrease

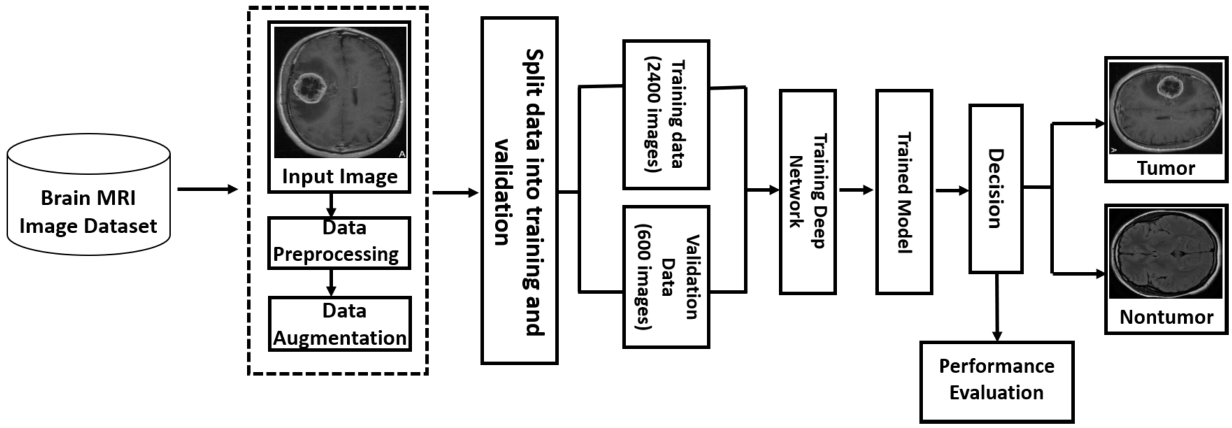

FIGURE 1. Block diagram of the proposed methodology.

the prediction error. The binary cross-entropy and adam optimizer is used here to solve this specific problem.

A. EfficientNet BASELINE MODEL

EfficientNet is a CNN model developed by the Google Brain Team [32]. These researchers examined network scaling and found that optimizing network depth, width, and resolution can boost performance. To create a new model, they scaled a neural network to construct more DL models that yield much higher efficacy and accuracy compared to the previously used CNNs. For the ImageNet, EfficientNet performed large-scale visual recognition with accuracy and consistency. Compared to the most exemplary established algorithms, such as VGGNets, GoogleNet, Xception [33], ResNets, and InceptionResNet [34], this series of CNN architectures is around eight times smaller and six times faster to infer. EfficientNet-B0 uses a composite scaling method that creates different models in the convolution neural network family. The number of layers in a network corresponds to the network depth. The convolutional layer width is proportional to the number of filters it contains. The height and width of the input image determine the resolution. Figure 2 presents the latest EfficientNet-B0 baseline model that accepts a $224 \times 224 \times 3$ input image. This algorithm captures characteristics across layers using numerous convolutional (Conv) layers with a 3×3 receptive field and the mobile inverted bottleneck Conv. Equation (1-5) illustrates how the authors propose scaling the depth, width, and resolution regarding ø.

$$d = \alpha^{\phi}, \tag{1}$$

$$w = \beta^{\phi}, \tag{2}$$

$$r = \gamma^{\phi}, \tag{3}$$

$$\text{s. } t \quad \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2, \tag{4}$$

$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1. \tag{5}$$

where d, w, and r denote the network's depth, width, and resolution, respectively, and the constant terms α, β, and γ were determined using the grid search hyperparameter tuning technique. The coefficient is a user-defined variable that manages all model scaling resources. This technique adjusts network depth, width and resolution to optimize network accuracy and memory consumption based on available resources. Unlike other deep CNNs, EfficientNet-B0 adjusted each dimension using a predefined set of scaling coefficients, outperforming other cutting-edge models trained on the ImageNet dataset. Even with the transfer learning technique, EfficientNet produced outstanding results and demonstrated its utility beyond the ImageNet dataset. The model was released with scales ranging from 0 to 7, indicating an increase in the parameter size and accuracy. With the recent development of EfficientNet, developers and users can now utilize and provide improved ubiquitous connectivity endowed with DL capabilities in different platforms to meet various needs.

B. PROPOSED LAYERS

This work is primarily related to implementing the EfficientNet-B0 model with the updated last layers inserted through layer freezing by fine-tuning and training to solve the problematic classification and detection of brain cancers in MR images. After performing data enhancement and augmentation to images measuring $224 \times 224 \times 3$, the images were sent into the pre-trained EfficientNet-B0 model, which automatically extracted the features. These characteristics could be color and shape descriptors like edges, circularity, roundness, and compactness. Figure 3 represents the proposed final layers for the EfficientNet-B0 composed of flattening, dropout, two fully connected (FC) layers, and a sigmoid classifier. We directed the feature sets from the sixth MBConv layer and converted them into a 1D array using a flattened layer. After flattening, it is passed to a dense layer with 128 hidden units. We used rectified linear unit ReLu as an activation function coupled to another dense layer with one neuron representing our provided labels before predicting the results. This method generated a probability by linearly applying a fresh set of weights and biases to each feature map. In addition, we used a dropout layer with a 20% rate after the hidden layer of 128 neurons to eliminate the overfitting

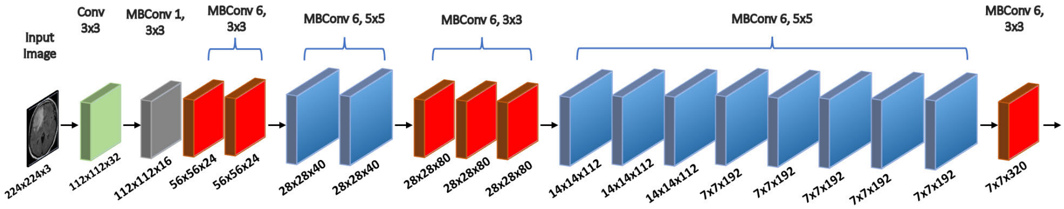

FIGURE 2. Baseline EfficientNet model architecture.

problem. We used sigmoid [35] as our final selected classifier. Equation 6 shows the mathematical function of a sigmoid classifier with a recognizable S-shaped curve. Sigmoid is a logistic function that performs a binary classification. It assigns values to 0 or 1 by setting up the threshold value of 0.5, where 0 represents non-tumor and 1 represents tumor images. The neuron at the last dense layer represents these classes.

$$f(x) = \text{Sigmoid}(x) = \frac{1}{1+e^{-x}}. \tag{6}$$

C. TRANSFER LEARNING AND FINE TUNING

This section demonstrates how we trained and refined our model. Figure 4 demonstrates our proposed finalized model. First, the Keras library has imported a pre-trained EfficientNet-B0 base model trained on the ImageNet dataset. The pre-initialized weights from ImageNet allowed the base model to use its features and enhance image recognition capability immediately. The weights obtained by training with the ImageNet dataset include features that can assist in detecting shapes, edges and other essential components required for image classification [36]. This strategy accelerated the process while requiring less work than arbitrarily initialized weights. The EfficientNet-B0 base model trained on the ImageNet data consisted of 1000 different classes and over 14 million images. Consequently, the current structure of EfficientNet-B0 could not be employed for our chosen task, and thus, fine-tuning was required [37]. We then froze all layers of the base model before fine-tuning our proposed end layers with the brain tumor MR image training data. With this method, we were able to keep the feature extraction capability in the weights obtained by training with the ImageNet dataset within the extraction layers and prevent them from being overridden during the training iterations. After training both the classifier and our recommended layers, we unfroze the complete layers of our network with weights obtained from the brain tumor MR image dataset and the ImageNet dataset weights to combine and construct our final model. Next, we used our test data to validate the final model.

D. HYPERPARAMETERS AND LOSS FUNCTION

This section describes the hyperparameter settings and loss function settings chosen for the task to produce efficient outcomes. The performance of a DL model depends not only on accuracy but also on loss [38]. The fundamental goal of a DL model is to achieve the absolute lowest rate of errors, considering that a model with a lower computed loss is more efficient. We used cross-entropy (CE) to obtain the average measure of the difference between the expected and predicted values. The loss measurement for the binary classification is shown in Equation 7, where y represents binary values of 0 or 1, and p represents the probability [39].

$$CE = -(y\log(p) + (1-y)\log(1-p)). \tag{7}$$

We chose Adam [40], as our optimizer to achieve the best possible loss reduction during training. This optimization technique uses an adaptive gradient descent function to assist the weights in more quickly approaching the local minima. Compared to alternative optimization techniques, such as SGD [41], or RMSProp [42], we selected Adam because of its ease of implementation, efficient memory use, and faster learning process. Adam recently had excellent DL applications that trained models for assistance in medical imaging analysis [43]. Table 1 presents the values of hyperparameters, with a small learning rate (LR) adjusted to function with the other hyperparameters. Adam efficiently and more quickly operated to reach a rapid convergence. The batch size of 32 allowed us to send information over the network without using up all of our computational memory. Furthermore, we used fixed durations to train each model to watch how it would react after 50 epochs.

TABLE 1. Training Hyperparameters and loss function for training.

Sr. no	Hyperparameters	Values
1	Optimizer	Adam
2	Initial LR	$10e^{-3}$
3	Reduced LR	$10e^{-5}$
4	Batch size	32
5	Epochs	50
6	Loss function	Binary cross-entropy

IV. IMPLEMENTATION DETAILS

A. DATASET DESCRIPTION

The dataset contained 3762 MR images, 3060 were used as a subset, and 1500 were labelled as 1 (tumors). The other 1500 scans were labelled as 0 (non-tumor). In order to avoid class dominance, the dataset was equally divided between the two classes, with 80% (2400) of the images going for training and 20% (600) going for validation [44].

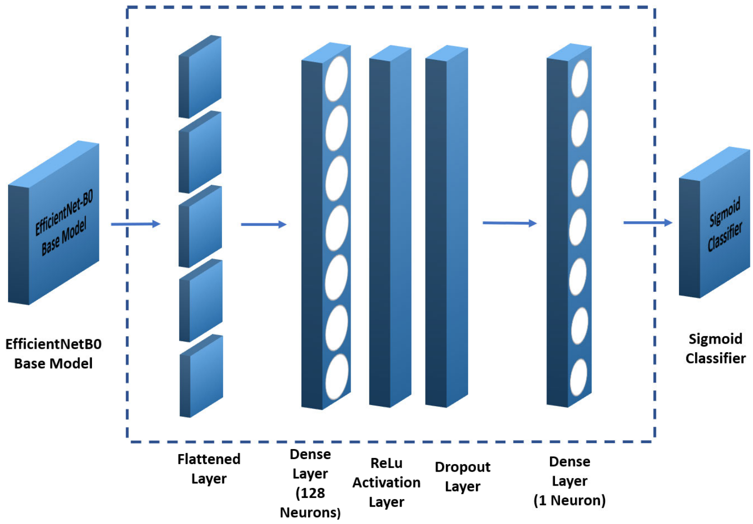

FIGURE 3. Schematic diagram of the proposed layers.

Furthermore, 60 images are used to test the proposed model's evaluation. Our subset selection depends on removing images that may have misled the model training. The image collection has no fixed dimensions. Therefore, all image samples are normalized and resized using an automated resizing script from Keras that automatically resized all the input images into 224 × 224 dimensions. The images dataset used in these experiments is an open-source dataset available on Kaggle. The dataset is a subset of the authorized benchmark Brats2015 brain tumor dataset, and the challenge database includes completely anonymized images from The Cancer Imaging Archive [45], [46].

B. DATA PREPROCESSING

Preprocessing the images will transform the data into a standard classified format. In the first step, the images were converted to grayscale with a constant pixel resolution of 224 × 224. Second, the images were blurred using Gaussian blur to reduce noise and increase the output quality. These photos were then processed through a high pass filter, which sharpened the picture and allowed the extraction of more complex features. Image processing techniques like erosion and dilation eliminate pixel intensities in too tiny regions to carry the structuring element. Erosion is the process of removing pixels from the edges of objects. After eroding the white areas (e.g., tumors), the volume was reduced, while the gaps, especially the holes in the white areas, grew in size. Dilation works opposite to erosion and adds pixels to the edges of structures. After dilation, the white areas increased in size due to extra white pixels on the edges. Meanwhile, the gaps in the white regions were filled. In the last step, We removed the black portions of each image. For these operations, contours were detected from the top, bottom, left, and right directions based on the presence of black regions. Figure 5 represents the preprocessing steps used in image cropping.

C. DATA AUGMENTATION

The effectiveness of most ML and DL models is determined by the quality, amount, and relevance of training data. However, one of the most prevalent problems in applying machine learning in organizations is a lack of data. It is due to the fact that gathering relevant data may be costly and time-consuming in many circumstances. Data augmentation is a series of methods for artificially increasing the quantity of data by producing additional data points from current data. It is a quick and efficient way to expand the dimensionality of training data and improve generalization to new unseen samples by making minor data modifications or deep neural networks to generate additional data samples. Data augmentation is popular in computer vision and natural language processing, signals, and speech domains [47]–[49]. In computer vision, the original dataset's augmentations undergo several image transformations to increase the data samples, which helps better train models and decrease overfitting. These operations include geometric transformations, flipping, color space, random cropping, random rotations, and noise injections. Models trained in this manner are more generalizable and generate better predictions from distributions other than the training data [50]. The image augmentations were performed by employing an open-source python library named Albumenatations to enhance the size of the dataset by creating a new set of images via various transformation methods such as random rotation (90°, 180°, 270°), horizontal, and vertical flips, and transposition [51]. The goal of employing Albumenatations was to preserve pixel-by-pixel information, essential for medical imaging tasks. The MR images were normalized using a Keras normalize function to transform

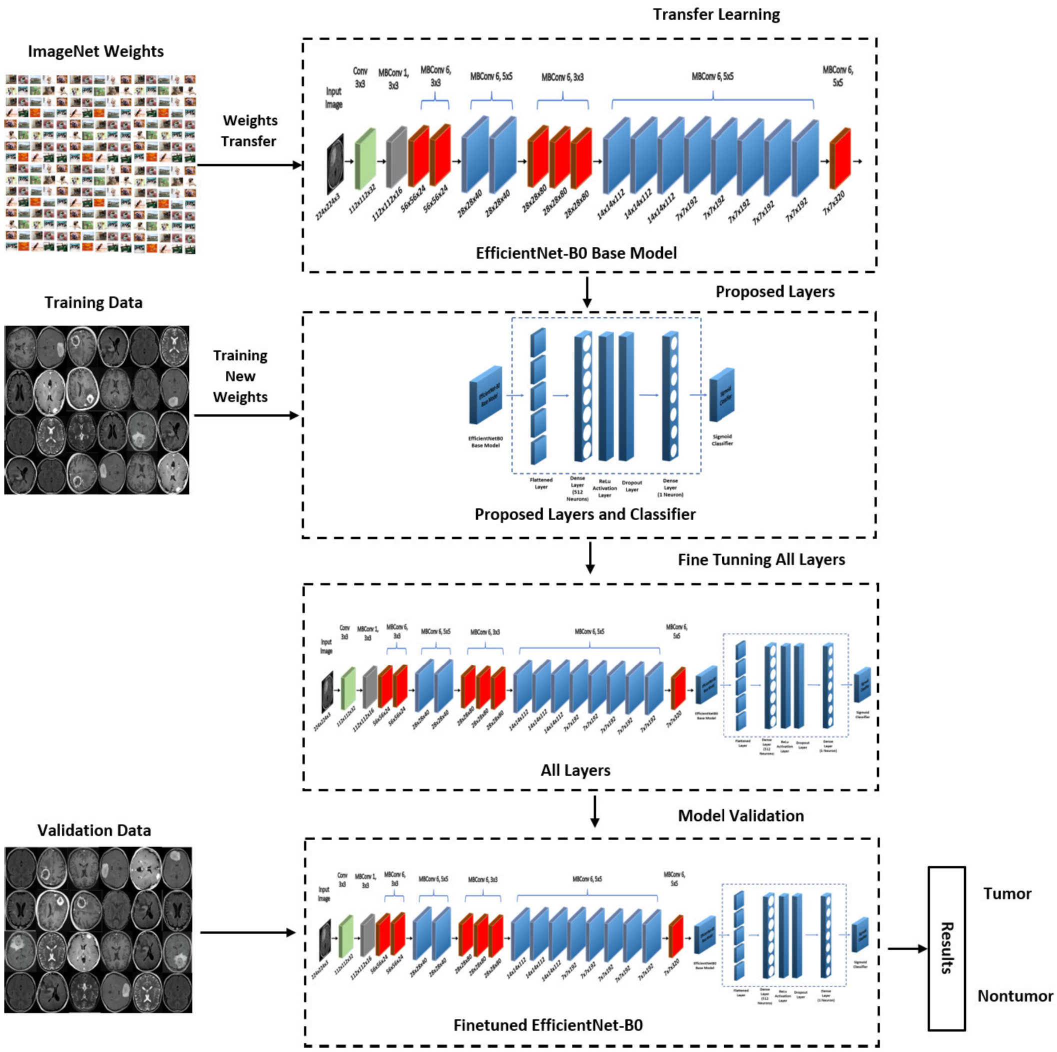

FIGURE 4. Detailed architecture of the proposed model.

each pixel value from 0 to 255 to a floating pixel range of 0 to 1.

D. EXPIREMENTAL SETUP

The proposed model was deployed on the open-access dataset. The fine-tuned EfficientNet model was implemented in Python using the Keras and TensorFlow frameworks as the foundation. The overall network was trained on a computer system with the following specifications: Intel Core i5-11400 CPU at 2.60 GHz. Our system had a 64-bit operating system with 16-GB memory, and 1 TB HDD, 128 GB SSD. The experiments were conducted using an NVIDIA RTX A5000 GPU. Table 2 presents the complete details. First, we imported the pre-trained EfficierntNet-B0 network from Keras and froze the beginning layers of the base model. In the second phase, fine-tuning was performed with our proposed ending layers with the brain tumor MR images, and the complete network was re-trained. The proposed and other CNN models were also compared to validate our experiment. Some of the validation procedures will be discussed in Section 6 for the specific dataset used herein.

TABLE 2. System specification used for the implementation.

Sr. no	Name	Experiment Parameters
1	System type	Windows 10, 64 bit
2	CPU	Intel Core i5- 11400 CPU at 2.60 GHz
3	GPU	Nvidia RTX A5000 24 GB GDDR6
4	Memory	16 GB
5	Development tool	Python 3.7
6	Library	TensorFlow

E. PERFORMANCE EVALUATION METRICS

The confusion matrix (CM) is a standard method representing how well a trained model could predict a given validation dataset. The CM has equivalent rows and columns indicating the actual class and the ground truth labels (i.e., tumors or non-tumors). Similarly, the predicted values represent the number of correct and wrong predictions or classifications for

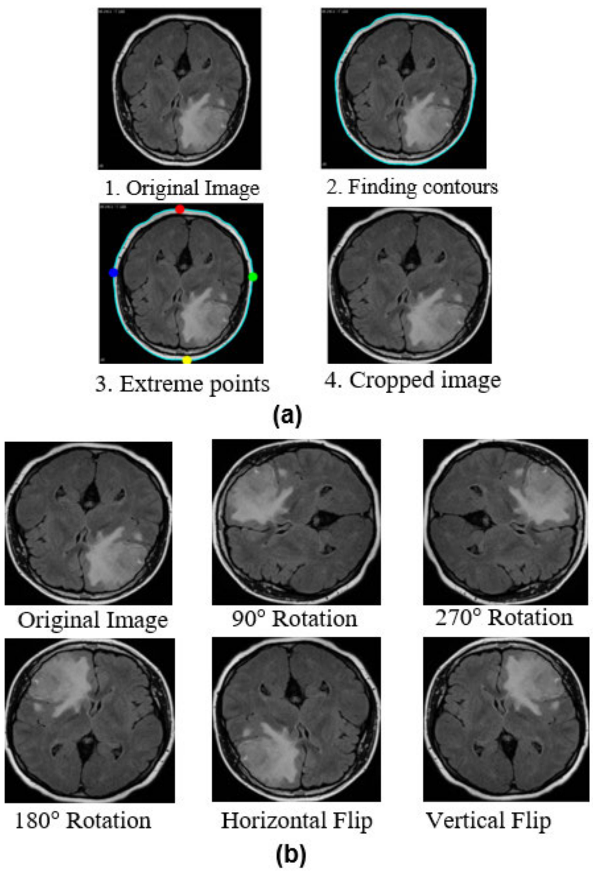

FIGURE 5. Data preprocessing and augmentation results. Figure5(a) shows the preprocessing steps. Figure 5(b) illustrates the data augmentation applied on magnetic resonance images.

each validation sample. True Positive specifies the number of correctly identified positive samples as positive, whereas True Negatives indicate the number of accurately predicted negatives as negatives. False Positives are predictions in which the image was labelled as positive; however, it was not positive. False Negatives are negative results that appear to be positive [52]. The performance of the AI-based models was assessed using numerous metric measures such as validation accuracy, precision, recall, F1 score, sensitivity, specificity, and area under the receiver operating characteristic curve. We calculated the overall accuracy, precision, sensitivity, specificity, and F1- score of each model using the equations (8 - 12) below:

$$Precision = \frac{TP}{TP + FP}, \tag{8}$$

$$Sensitivity = \frac{TP}{TP + FN}, \tag{9}$$

$$Specificity = \frac{TN}{TN + FP}, \tag{10}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{11}$$

$$F1Score = \frac{2(TP)}{2(TP) + FP + FN}. \tag{12}$$

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. PROPOSED MODEL RESULTS

This section discusses the results generated during the training and the validation of the proposed fine-tuned EfficientNet-B0 model trained on the MR images taken from open access from Kaggle. Several preprocessing and data augmentation techniques were applied to enhance this particular dataset's quality and size. For better training, we used a variety of hyperparameters to train our proposed model. We used Adam optimizer with an initial learning rate of $10e^{-3}$, ReduceLROnPlateau callback with a minimum learning rate of $10e^{-5}$, batch size of 32, and CE loss function. A sigmoid classifier was employed as our final selected classifier. Meanwhile, the Keras API with a backend TensorFlow was used to train our fine-tuned EfficientNet architecture. The proposed model was trained to use 80% data for training and 20% for validation. Figure 6 represents the training results and validation results. Figure 7 represents the loss curves with training epochs. For the proposed model, the graph illustrates that the accuracy of the validation and training sets steadily grew in a shorter period with the given hyperparameters as the number of epochs increased until it reached a point of stability.

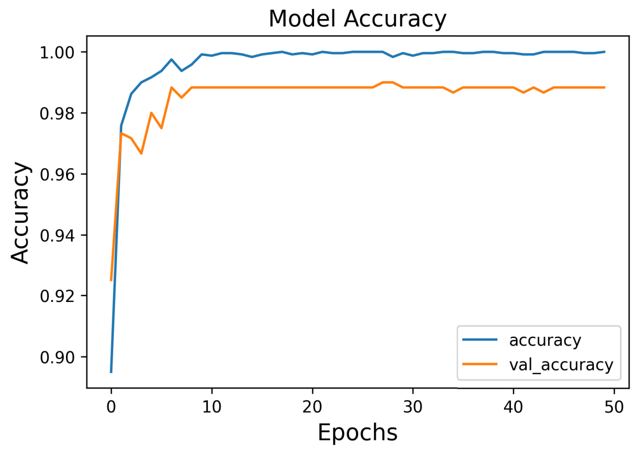

FIGURE 6. Training and validation accuracy curves of the proposed model.

To evaluate the performance of our proposed model, a CM was used to identify the number of correctly classified and misclassified data and estimate the performance using the evaluation metrics mentioned above. Figure 8 shows that the CM of the proposed model successfully identified 225 images as tumors while failing to detect two images. The second-class model correctly identified 338 images as non-tumor and failed to detect five images. Figure 9 displays the evaluation metric score of the proposed model.

Figure 10 depicts the Receiver operating characteristic (ROC) curve that characterizes the performance of our brain tumor detection model. The area under the curve (AUC) is a crucial assessment parameter for different classifiers, indicating the degree of distinction across classes. It demonstrates how well the model differentiates across categories.

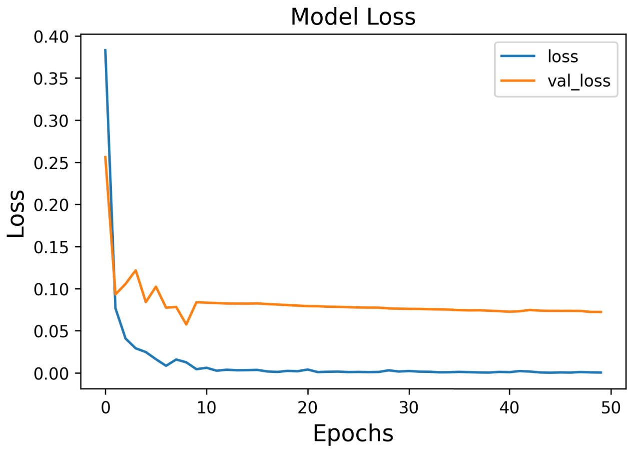

FIGURE 7. Training and validation loss curves of the proposed model.

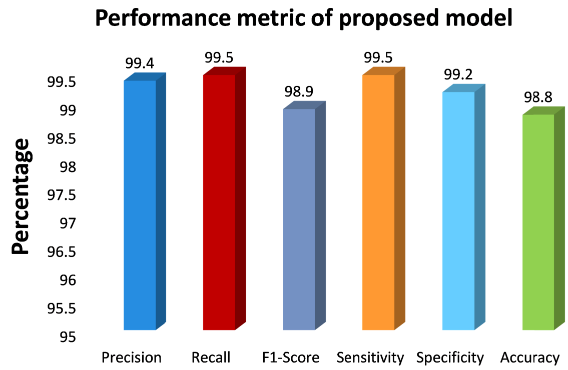

FIGURE 9. Evaluation metric score of the proposed model.

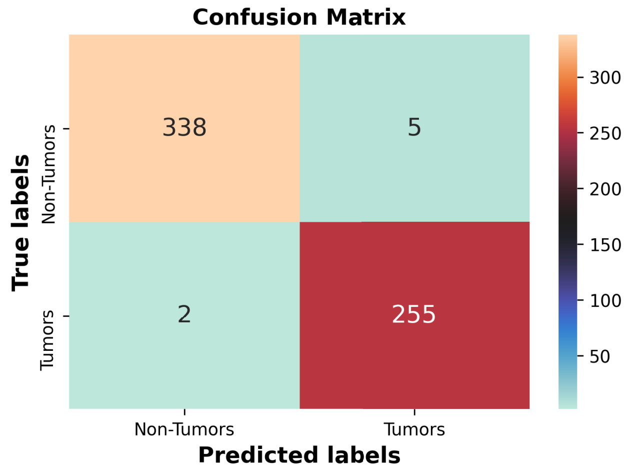

FIGURE 8. Confusion matrix of the proposed EfficientNet-B0 model.

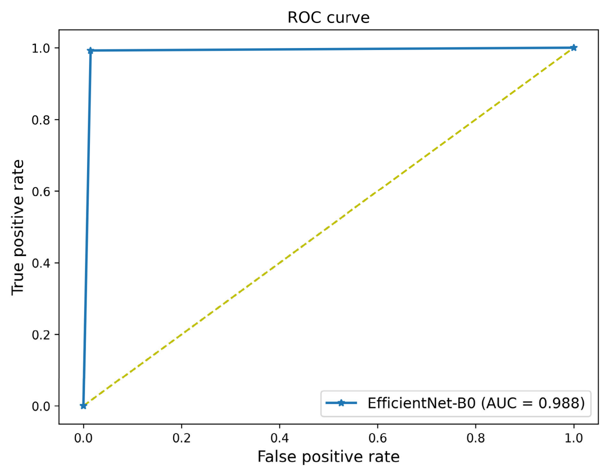

FIGURE 10. Receiver operating characteristic plot of the proposed EfficientNet-B0 model.

The greater the AUC, the better the model can distinguish between patients who suffer and do not suffer from the condition. An efficient model with an AUC close to 1 indicates a high competence level. It can be observed that EfficientNet-B0 showed an AUC value of 0.988.

As shown in Figure 11(a) the proposed model correctly classified the brain MR images. If the image contains a tumor (True: 1), the model predicts that it contains a tumor (Pred: 1); however, if the image does not contain a tumor (True: 0), the model assumes that it has no tumor or is a regular image (Pred: 0). Figure 11(b) illustrates how the proposed model misclassifies the brain MRI images. If an image has a tumor (True: 1), the model assumes it does not have a tumor (Pred: 0). If it does not have a tumor (True: 0), the model predicts that it has a tumor (Pred: 1).

B. COMPARATIVE ANALYSIS OF PROPOSED MODEL WITH THE RECENT STATE-OF-THE-ART METHODS

This study compared the performances and efficiencies of six CNN architectures: VGG16, GoogLeNet, InceptionResNetV2, Xception, ResNet50, and EfficientNet-B0. Each deep CNN in each study employed the same set of parameters (Table 1) and features that varied according to the depth of the convolution layer and the FC layers. Table 3 shows the validation accuracy for the fine-tuned proposed network and other pre-trained DL models used in this study. It also reports the other calculated evaluation metrics. All models showed a minimal error gap at the end of each phase, except for InceptionResNetV2, which had a slight overfitting problem at the beginning. All the other models showed a very stable minimization of loss.

In the first study, EfficientNet-B0, a deep neural network developed by Google AI, with our proposed layers, was employed to investigate the transfer learning approach for detecting the brain tumors in MR images. The proposed fine-tuned EfficientNet-B0 network achieved the highest (98.87%) accuracy on the validation data by outperforming the other networks discussed below. In the second study, the VGG16 architecture developed by the Visual Geometry Group was employed to investigate the effectiveness of the transfer learning approach in detecting the brain tumors in MR images. The fine-tuned VGG16 network achieved 98.64% accuracy on the validation data. The InceptionV3

TABLE 3. Comparison of the performances of the proposed model and other fine-tuned models.

Models	Precision%	Recall%	F1-Score%	Sensitivity%	Specificity%	Accuracy%
VGG16	98.5	99.1	99.1	98.8	98.5	98.6
InceptionV3	97.7	97.6	96.4	97.6	97.4	97.5
Xception	96.6	98.5	97.5	98.5	97.3	97.8
ResNet50	97.6	98.2	97.9	98.2	96.3	97.6
InceptionResNetV2	97.6	98.4	98.0	98.4	98.3	98.3
Proposed EfficientNet-B0	**99.4**	**99.5**	**98.9**	**99.5**	**99.2**	**98.8**

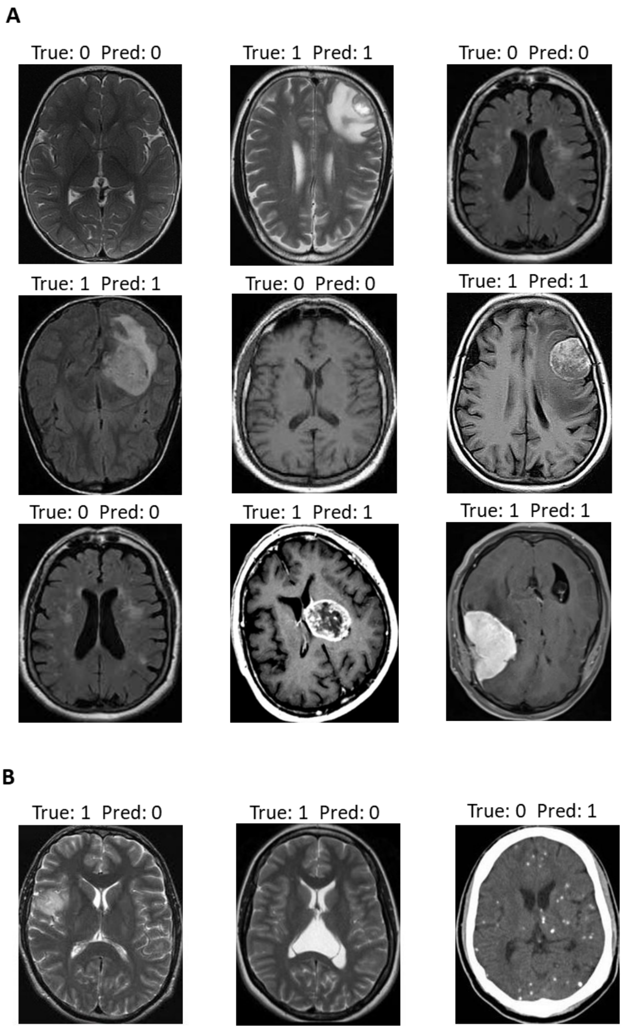

FIGURE 11. Results of the proposed EfficientNet-B0 architecture on the testing data. Figure 11(A) shows the correct classified results of the proposed model. Figure 11(B) illustrates the misclassified images of the proposed model.

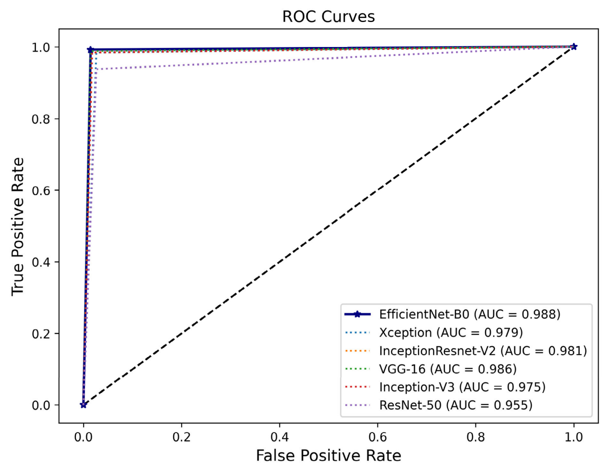

FIGURE 12. Receiver operating characteristic plot for the proposed EfficientNet-B0 and other convolution neural network models with the area under curve values.

TABLE 4. Comparison of the accuracies of the proposed and previous state-of-the-art ML and DL methods.

Related Work	Model	Accuracy%
Latif et al. [17]	SVM	96
Khan et al. [19]	VGG-19	94
Yahyaoui et al. [20]	DenseNet	92
Bhatele et al. [22]	Hybrid Ensemble	95.2
Murthy et al. [23]	CNN Ensemble	95
Ours	**FT EfficientNet-B0**	**98.8**

study model developed by the Google team was deployed to investigate the transfer learning approach to detect brain tumors. It obtained a validation accuracy of 97.5%. The Xception, developed by the Google team, was used to show the model's efficacy by achieving an overall 97.8% validation accuracy. Meanwhile, the InceptionResNetV2 algorithm achieved 98.33% accuracy on validation data. Also, a pre-trained version of ResNet50 developed by the Microsoft team was used to detect the brain tumors in MR images. The results for the ResNet50 algorithm showed the lowest 95.8% accuracy on the validation dataset among all the tested models in this specific study, which is average.

The examination and the comparison of the results of each structure using the fine-tuned technique. (i.e., Table 3 and Figure 12) showed that all CNNs dominated by the proposed model with a minor difference. The proposed EfficientNet-B0 model achieved the highest accuracy among the six CNN designs by generalizing the brain tumor images.

Table 4 provides a performance review of this study and other current studies that used ML and DL based solutions for brain tumor detection. Note that this research does not directly compare the following studies due to differences in data preparation, training and validation methodologies, and computational power used in their methods. However, we observed that the proposed model produced an excellent

TABLE 5. Comparison of the weight size and parameters with recent state-of-the-art models.

Models	Weight Size(MB)	Parameters(M)
Proposed EfficientNet-B0	**16.8**	**8,028**
VGG16	56.5	17,092
InceptionV3	83.6	28,356
Xception	87.1	33,096
ResNet50	93.8	36,410
InceptionResNetV2	210	60,252

performance in terms of accuracy by achieving 98.87% overall accuracy.

C. WEIGHT SIZE AND PARAMETERS

This section discusses the weight size and number of parameters of different fine-tuned CNNs used in this research study. Table 5 depicts our generated weight sizes and the number of parameters. The following table shows that the proposed fine-tuned EfficientNet-B0 produced the smallest size of only 16.8MB with 8,028 different parameters, considering it one of the lightest weight and efficient models. Consequently, the VGG16 model has a weight size of 56.5MB and 17,092 parameters, and the InceptionV3 model has a weight size of 83.6MB, and the total number of parameters is 28,356. Next, Xception produced a weight size of 87.1MB with a 33,096 total number of parameters. For the other models, Inception-ResNetV2 has the most prominent weight size of 210MB with 60,252 parameters and, ResNet50 with an overall weight size of 93.8MB and 36,410 total parameters.

VI. CONCLUSION AND FUTURE WORK

MR imaging for the detection of brain tumor research has gained significant popularity because of the rising requirement for a practical and accurate evaluation of vast amounts of medical data. Brain tumors are a deadly disease, and manual detection is time-consuming and dependent on the expertise of doctors. An automatic diagnostic system will be required to detect abnormalities in MRI images. Therefore, this study developed an efficient, fine-tuned EfficientNet-B0 based transfer learning architecture to identify brain cancers from MRI scans. The proposed technique achieved the maximum performance in brain tumor detection, with 98.87% validation accuracy. Although this study focused on five other convolutional models and transfer learning designs for brain tumors in the medical imaging field, further research is needed. We will investigate more significant and influential deep CNN models for brain tumor classification and conduct segmentation with reduced time complexity in future approaches. Also, to improve the accuracy of the proposed model, we will increase the number of MRI scans in the dataset used for this study. Furthermore, we will also be applying the proposed approach to other medical images such as x-ray, computed tomography (CT), and ultrasound which may serve as a foundation for future research.

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