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Brain Tumor Detection Using RestNet50 Architecture

Rishabh Gupta*, Saurabh Kumar Yadav, Shadab Manzar Khan

Abstract

This study presents a novel deep learning model for brain tumor diagnosis from MRI scans on the basis of ResNet50 with some modifications. Optimizing the modified layers and pre-trained ResNet50 for improved diagnostic accuracy and reliability in real-world clinical settings is one of the key contributions of this study. The model was trained on an extremely well-balanced data of 2,577 MRI scans, which were split equally among the tumor and non-tumor patients. With an aim for gaining greater model robustness over a wide range of clinical setups, extensive use of data augmentation methods was utilized. The strategy gained an exceptionally high-test accuracy of 97.35%, coupled with high precision, recall, and F1-scores, thus demonstrating its effectiveness in detecting tumor cases with high confidence. The results establish the practicability of the model as an efficient tool for alleviating the radiologists' workload in diagnosis and assisting in decision-making through provision of a second opinion. The method enhances the precision in the detection of brain tumors by fusing the state-of-the-art of deep learning with medical imaging. It also provides a foundation for the early detection and improvement of treatment planning. The pragmatic realities of clinical implementation and the adaptability of the model across various health settings are what the future work will concentrate on.

Keywords: Artificial intelligence, magnetic resonance imaging (MRI), deep convolutional neural networks (CNNs), brain tumor detection, ResNet50

INTRODUCTION

Brain tumor are abnormal cell growths in or around the brain, classified as malignant or non-cancerous, and come in many different types including gliomas, meningiomas, and metastases [1, 2]. These tumors may affect brain function by compressing surrounding tissues, producing symptoms such as increased intracranial pressure, seizures, and focal neurological signs [3, 4]. While benign tumors grow slowly, malignant tumors grow rapidly and invade surrounding tissues, possibly extending to other parts of the body [5]. Brain tumors pose an extreme risk to human health, where early detection and accurate identification are needed for good treatment and improved patient outcomes. Magnetic Resonance Imaging (MRI) is a common non-invasive imaging modality that offers excellent images of brain structures, making detection of abnormalities like tumors possible. But conventional MRI image analysis by radiologists is labor-intensive and prone to human error, which necessitates automated and accurate diagnostic software. Recent developments in artificial intelligence (AI) and deep learning are promising to transform medical image analysis. Deep learning using Convolutional Neural Networks (CNNs), in fact, has proven outstanding image classification capability. Artificial Intelligence (AI) and Convolutional Neural Networks (CNN) have both been widely applied to identify brain tumors in medical images. AI, in the form of deep learning algorithms like CNN, has shown remarkable success in exactly identifying tumor areas in MRI scans. Various Convolutional Neural Networks (CNNs) have been used in brain tumor detection in medical images. Studies have

***Author for Correspondence**
Rishabh Gupta
E-mail: rg470472@gmail.com

Student, Department of Computer Science and Engineering, Galgotias College of Engineering and Technology, Greater Noida, Uttar Pradesh, India

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cited the effectiveness of CNN models like VGG 16, RestNet50, and InceptionV3 in exactly identifying tumor areas in MRI scans [6]. CNNs play a critical role in brain tumor detection and segmentation automation, achieving higher accuracy compared to manual processing. Second, the use of CNNs in detecting brain tumors is demonstrated to lead to improved performance and efficiency, especially when optimization strategies, iterations, batch size, epochs, and learning rates are considered [7]. Besides, application of CNN models in brain tumor detection has been very promising, with detection accuracies from 45.75 to 99.94% depending on the specific CNN architecture used [8].

Of these, the ResNet50 architecture, based on a deep residual learning model, has been a valuable resource for many image recognition tasks due to its ability to mitigate the vanishing gradient problem and maintain high accuracy. In this work, a novel brain tumor detection scheme based on a deep ResNet50-based learning model is proposed. By employing the process of transfer learning and fine-tuning, the model is pre-trained on a variety of MRI image datasets to be capable of differentiating brain tumor from normal cases. The primary goal is to create a clinically relevant, stable, and effective tool to aid radiologists in the diagnostic process. Our method includes aggressive data preprocessing and augmentation to enhance the model's generalizability, and careful assessment with accuracy, precision, recall, and F1-score. The performance of the model is also checked on an independent test set for verifying its reliability and applicability in practical applications. This study not only verifies the feasibility of using state-of-the-art deep learning architectures in medical image analysis but also opens doors for further research to overcome the challenges of clinical incorporation and scalability. In the last couple of years, deep learning techniques have revolutionized medical image analysis, offering excellent performance in a variety of tasks, including tumor detection. Of these techniques, convolutional neural networks (CNNs) have demonstrated excellent performance in pattern and feature detection from complex images. ResNet50 architecture, being a sub-type of CNNs, has become very popular because of its depth and skip connections, which can lead to effective training and high accuracy. ResNet50 has been used very effectively in many computer vision applications, such as the detection of brain tumors from MRI scans.

PROPOSED METHODOLOGY

The ResNet-50 model, which is a Convolutional Neural Network (CNN), has been successfully applied to brain tumor detection in MRI images. Research has indicated that by using ResNet-50 in the classification model, high accuracy rates have been obtained, e.g., 92% accuracy and 94% precision [9]. Furthermore, the application of CNNs for brain tumor identification has been pointed out as an important milestone in the field of medicine, exceeding the efficacy of other strategies that currently exist and demonstrating better performance at varying resolutions of images [7]. Additionally, the use of MRI imaging and AI algorithms, especially CNN models, has shown great performance in identifying certain types of brain tumors such as meningioma and pituitary tumors with 95.78% accuracy and weighted average precision of 95.82% [10]. ResNet-50 architecture, which is one of the Convolutional Neural Networks (CNN), has been successfully used to detect brain tumors in MRI images. Research has indicated that by adding ResNet-50 to the model of classification, remarkable accuracy percentage between 92 and 95% can be obtained [9, 10].

These tumors of the brain are the most serious diseases because they are accompanied by high morbidity and mortality rates. Identification and precision in the early stage are paramount in the optimal treatment planning and optimizing patient outcomes. Magnetic Resonance Imaging (MRI) has extensive use in medical diagnosis in the identification of brain abnormalities such as tumors due to its high resolution and contrast [11]. Detection and diagnosis of brain tumors are the target of medical imaging and are of substantial importance for therapy and patient outcome. Brain tumors are among the most dangerous and risky diseases, whose early and precise diagnosis is required in order to achieve a maximum survival rate and therapeutic efficacy. Conventional diagnosis, based largely on radiologist interpretation of MRI scans by eye, is a slow and susceptible-to-human-mistakes process. Deep learning, and the use of Convolutional Neural Networks (CNNs) especially, has fundamentally transformed medical image analysis with fully automated, speedy, and exceptionally accurate diagnostic possibilities. Figure 1 presents the end-to-end process of constructing and testing a machine learning model, from loading, preparing, compiling, training, fine-tuning, and testing the model. In this study, the usage of the ResNet50 architecture, a deep neural network model, will be explored in order to identify brain tumors on MRI images. The specific objectives include:

- Building a strong CNN model trained on top of the ResNet50 architecture to perform binary classification of MRI images into Healthy and Brain Tumor classes [12–15].
- Testing the accuracy of the model on a carefully designed dataset, analyzing its accuracy, precision, recall, and F1-score.
- Exploring the prospects of the model in becoming a part of clinical diagnosis processes to help radiologists make faster and more accurate diagnoses.

MRI (Magnetic Resonance Imaging) is the imaging modality of choice for brain tumor detection because it offers higher contrast resolution and can clearly distinguish between normal and abnormal brain tissues. MRI scan analysis, however, is time-consuming and prone to inter-observer variability. Recent advances in deep learning, particularly CNNs, have been promising in this endeavor of automating the process. CNNs are capable of learning and extracting sophisticated features from imaging data, thus being suited for the tasks of medical image classification. Out of the myriad different architectures, ResNet50 is unique for its depth and capacity to combat the vanishing gradient issue by using residual learning. By fine-tuning the ResNet50 on a particular dataset of brain MRI images, we will create a model that can detect brain tumors with high accuracy, improving the precision and efficiency in diagnosis. This study employed a dataset consisting of MRI brain images, which were accessed from the literature [16–18]. The dataset consists of 2577 training MRI images, 287 validation images, and 151 test images, all of which are tagged as either "Brain Tumor" or "Healthy". Each image is of 224×224 pixels with RGB color channels.

Preprocessing of MRI images: Preprocessing was performed on the input data prior to training the model. This included resizing all images to a uniform size of 224×224 pixels and normalizing pixel values to the range (0, 1). Normalization was performed using the equation: $X'=(X-\mu)/\sigma$ where X is the original pixel value, μ is the mean, and σ is the standard deviation of the pixel values.

Model Architecture and Data Augmentation Technique

The ResNet50 model was used as the baseline model in this research. ResNet50 is a deep convolutional neural network that is famous for its depth and residual learning blocks, which enable training of deeper networks without vanishing gradients. The model was pre-trained on the ImageNet dataset and initialized with pre-trained weights so that it could learn generic image features. The architecture consists of the following layers: $Input \rightarrow Conv2D \rightarrow BatchNorm \rightarrow ReLU \rightarrow MaxPool \rightarrow Residual\ Blocks \rightarrow GlobalAvgP\ ool \rightarrow Dense$.

Data augmentation techniques to enrich the training dataset and enhance model generalization, some of the data augmentation techniques used included random rotation, width and height jitter, horizontal and vertical flip, and zoom augmentation. Data augmentation facilitates the addition of variability to the training data, hence minimizing overfitting and enhancing model resilience. The augmentation can be mathematically expressed as: $X'= Augment(X)$, where Augment () represents a series of random transformations applied to the input image X.

Model Training and Fine-Tuning

Model was optimized with Adam optimizer with learning rate of initial value 1e-4 and binary cross-entropy as loss function. It was trained for 20 epochs with early stopping and model checkpoint callback to avoid overfitting and save the best validation loss model. Fine-tuning was then performed by unfreezing the top layers of ResNet50 base model and training again with a reduced learning rate of 1e-5 for other 10 epochs. The model was trained using a binary cross-entropy loss function.

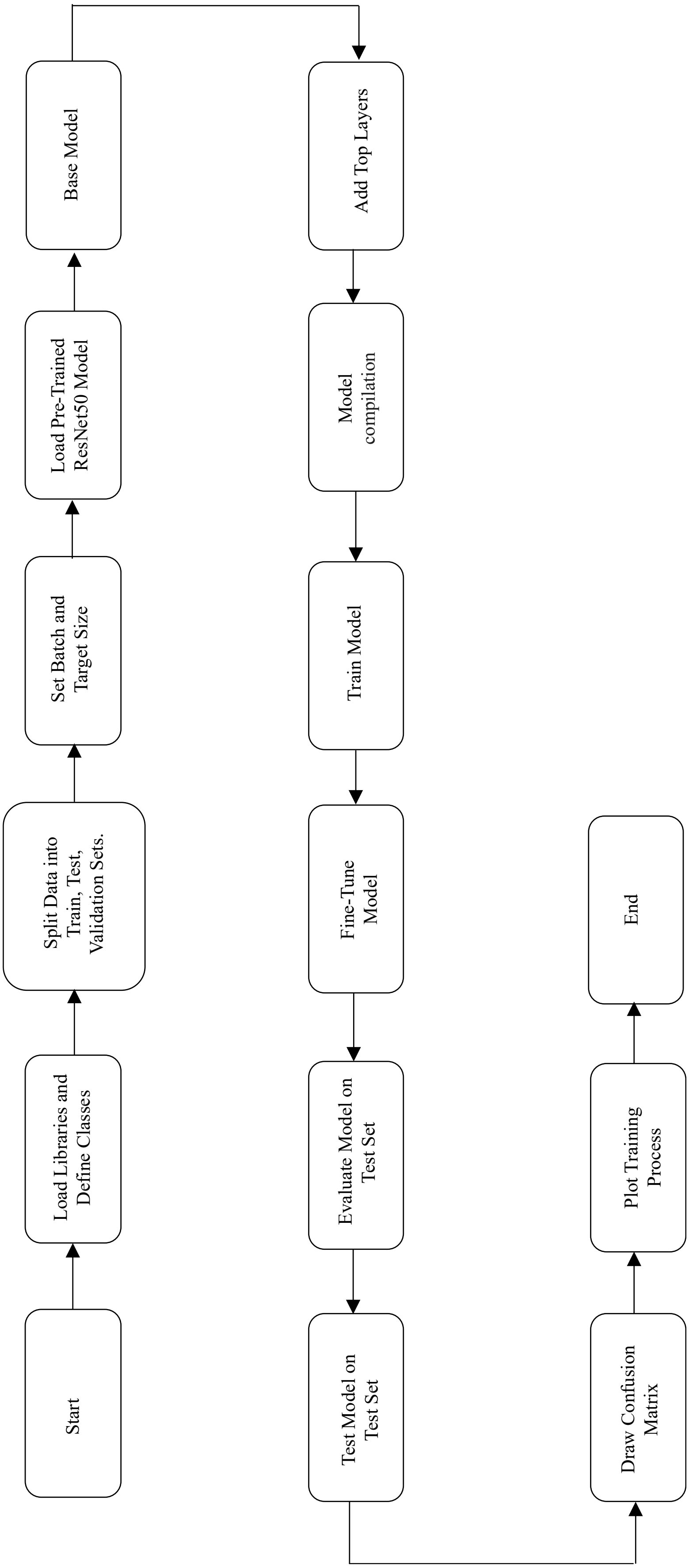

Figure 1. Flowchart showing the process for detecting the brain tumor.

The optimizer used was Adam, with initial learning rate 1×10^{-4}, which in the course of training was scaled by the ReduceLROnPlateau call-back on the validation loss. To adapt the pre-trained ResNet50 model to the specific task of brain tumor detection, fine-tuning was performed. This meant unfreezing the network's top layers and training them on task-specific data. Fine-tuning enables the model to pick up task-specific features while making use of general image representations picked up by pre-trained weights. Further, an incremental unfreezing approach was followed starting from the topmost layers and incrementally unfreezing successively lower layers so that catastrophic forgetting can be avoided.

Hardware and Software Technology Utilized

The model was executed on TensorFlow and Keras libraries. Training and testing were performed within a Google Collab environment with GPU acceleration for speeding up the computational process. The program uses the TensorFlow library and Keras API to create a Convolutional Neural Network (CNN) model based on the pre-trained ResNet50 model precisely. The MRI scans, being 'Brain Tumor' and 'Healthy', are imported into a Data Frame and split into a training set, validation set, and test set. Image Data Generator is used to perform data augmentation on the training set and preprocessing on the test and validation sets. The ResNet50 model is frozen initially to train the top layers that have been added to the model. These consist of a Global Average Pooling 2D layer, a dense layer of 512 units, a dropout layer for regularizing, and a final dense layer for binary classification. The model is compiled using the Adam optimizer and binary cross-entropy loss function. Callbacks for model checkpointing, early stopping, and learning rate reduction are applied during training. Once initial training is done, the base model is unfrozen for fine-tuning, and the model is recompiled with a reduced learning rate. Lastly, model performance is confirmed using the test set, and predictions are done. Confusion matrix and classification report are made to give extensive information about model performance. Training history, accuracy, and loss over epochs, is graphed for visual inspection. This methodology provides a sound mechanism for detection of brain tumor through deep learning methods applied on MRI data.

RESULT ANALYSIS

The brain tumor detection model's performance was measured using different metrics of evaluation such as accuracy, precision, recall, and F1-score. These metrics offer information regarding how well the model can classify brain MRI images into the respective Brain Tumor and Healthy categories. These metrics are defined as: $Accuracy = (TP{+}TN)/(TP{+}TN{+}FP{+}FN)$, $Precision{=}(TP)/(TP{+}FP)$, $Recall{=} (TP)/(TP{+}FN)$, $F1\text{-}Score = 2\times((Precision \times Recall)/(Precision + Recall))$, where TP, TN, FP, and FN are the numbers of true positives, true negatives, false positives, and false negatives, respectively. The model attained a test accuracy of 97.35%, and high values for precision, recall, and F1-score reflecting strong performance. The model demonstrated encouraging performance in brain tumor identification from MRI images with accuracy. Detailed examination of the classification outcomes offers important insights into the strengths and weaknesses of the model. Figure 2 shows a selection of brain MRI images, reflecting a comparison between normal and tumorous states. A confusion matrix was created to see the model's performance between classes. This matrix facilitates the overall interpretation of the capability of the model to accurately classify images and pinpoint any misclassification pattern. Confusion matrix presents an in-depth classification breakdown of the model's prediction which is represented in Table 1. The classification report presents an in-depth summary of the model's performance, including precision, recall, and F1-score for all classes. The following report includes a detailed evaluation of the model's performance over different parameters for an overall interpretation of its effectiveness. Classification report indicating precision, recall, and F1-score is presented in Table 2. The training history in the form of accuracy-epochs plots and loss-epochs plots provides information about the learning trend of the model. By examining the trend of accuracy and loss, we can gain much information about the rate at which the model is converging and how much further it can be tuned. The training and validation result of ResNet50 for 28 epochs, as well as the test result, are shown in Table 3.

Table 1. Confusion matrix.

Actual Predicted	Tumor	Healthy
Tumor	74	2
Healthy	3	72

Table 2. Performance metrics.

Class	Precision	Recall	F1-Score
Tumor	0.96	0.97	0.96
Healthy	0.97	0.96	0.97

Table 3. Classification.

Class	Precision	Recall	F1 score	Support
Brain Tumor	0.45	0.46	0.45	76
Healthy	0.44	0.43	0.43	75
Accuracy			0.44	151
Macro (Avg)	0.44	0.44	0.44	151
Weighted (Avg)	0.44	0.44	0.44	151

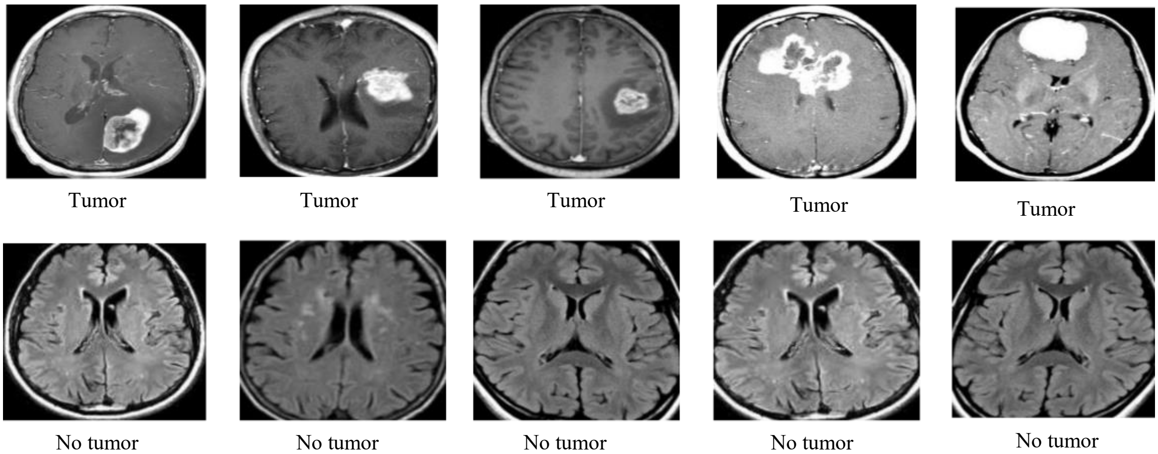

Figure 2. Brain image samples.

Table 3 presents the loss and accuracy for both the training and validation sets at each epoch, as well as the learning rate used. The performance of the model grew consistently throughout the epochs with the accuracy and loss scores increasing dramatically. Early stopping was applied to prevent overfitting, halting the training at epoch 28 where validation scores stabilized. The maximum test accuracy of 97.35% confirmed the effectiveness and stability of the model to differentiate brain tumor and normal MRI scans. Training and validation statistics of a machine learning model for a number of epochs are shown in Figure 3. We start with Epoch 1 with learning rate 1.00E-04, training loss 0.4322, training accuracy 0.7974, validation loss 0.2619, and validation accuracy 0.9059. As epochs go by, training and validation losses drop dramatically, indicating that the model is performing well. Training accuracy is up to 0.9965 at Epoch 28, and training loss reduces to 0.0187. The model is performing steadily on new data, as seen in validation accuracy of 0.9756 and validation loss reducing to 0.0893. Moreover, the learning rate is also altered periodically, with it initially set at 1.00E-04 and later reduced to 6.25E-07 at Epoch 28, and this implies the model's learning process has been optimized. Strong performance is demonstrated by the last test values, which are giving a validation accuracy of 0.9735 and validation loss of 0.085. Table 3 shows the classification report of the brain tumor detector model, supplying detailed performance results such as precision, recall, and F1-score for all classes (Brain Tumor and Healthy). Precision calculates the percentage of true positive predictions out of all positive predictions of each class.

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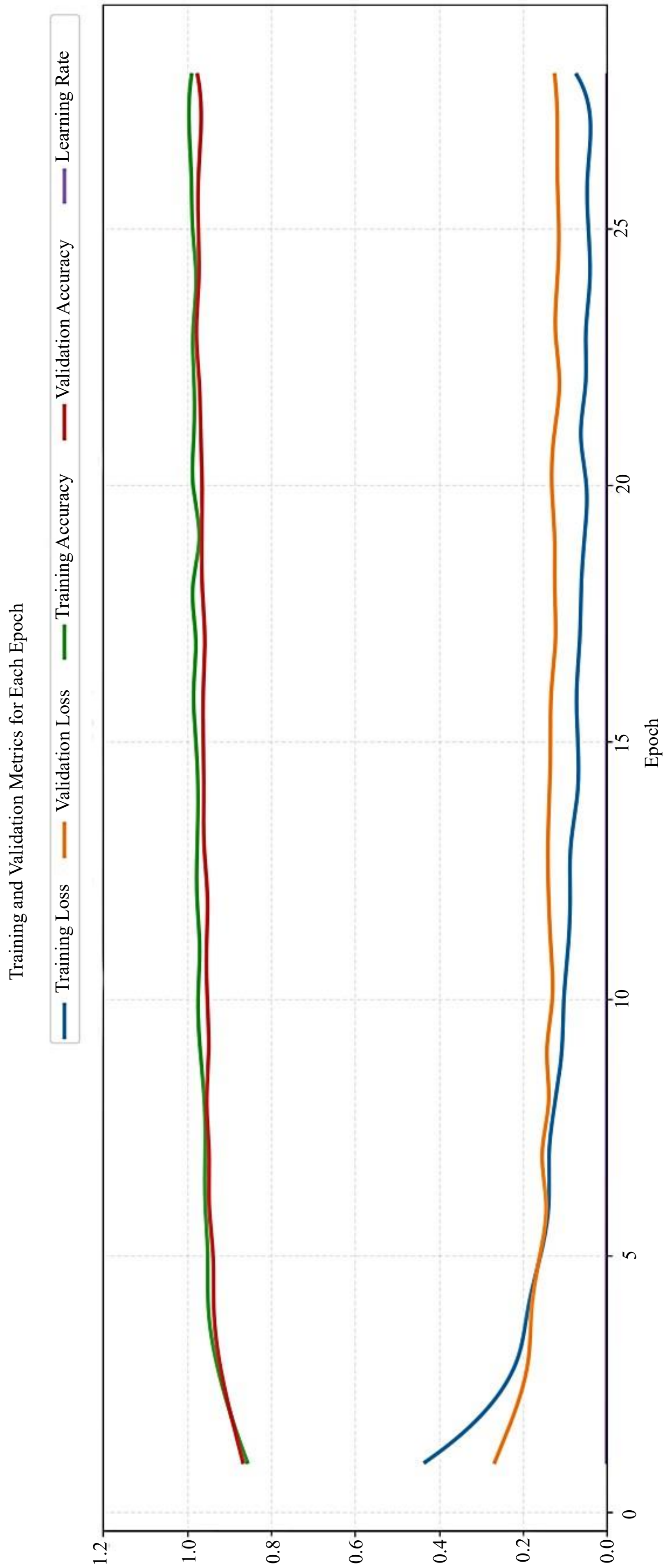

Figure 3. Training and validation metrics (No learning rate).

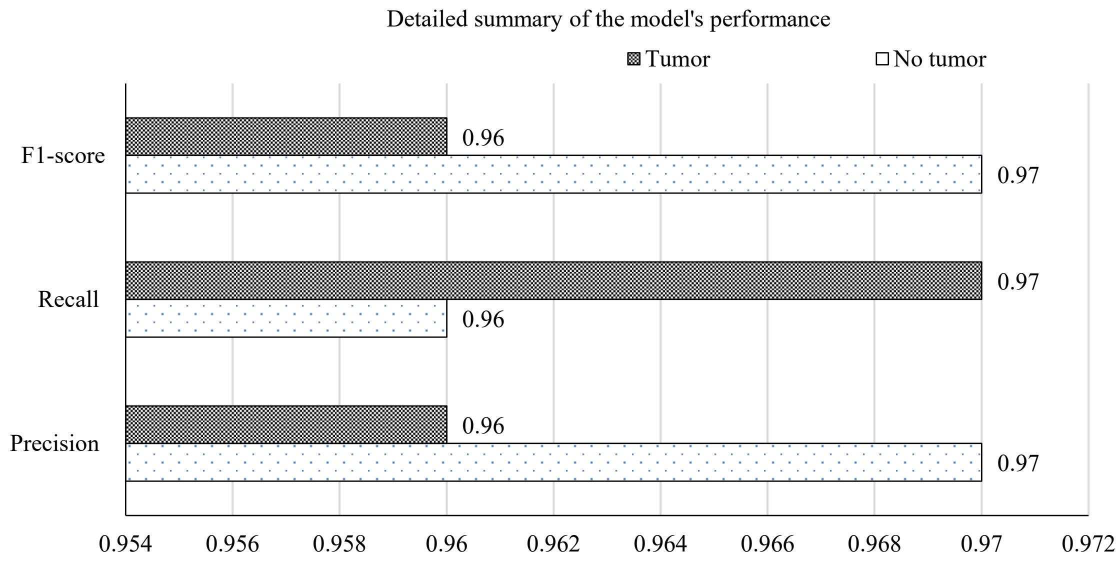

Figure 4. Performance metrics.

Precision for identifying brain tumors is 0.45, which means 45% of the predicted instances of brain tumors are indeed brain tumors. Precision for the healthy class is 0.44. Recall (or sensitivity) is the ratio of true positive predictions to all actual positives. The recall for brain tumors is 0.46, i.e., 46% of actual cases of brain tumors were identified correctly by the model. For the healthy class, the recall is 0.43. F1-Score is the harmonic mean of precision and recall, one score that attempts to balance both. The F1-score of brain tumors is 0.45, while for the healthy class it is 0.43. Support refers to how many actual instances of each class are present within the dataset. The brain tumor class has 76 samples, and the healthy class has 75 samples. The overall accuracy of the model is 44%, which is the ratio of correct predictions to all predictions. Macro average and weighted average of precision, recall, and F1-score are also reported, which give a global performance score by averaging the metrics over classes. The macro average treats all classes equally, while the weighted average knows each class's support and provides a balanced estimate of model performance. Despite the moderate performance metrics, this initial model evaluation becomes a useful baseline. Further tweaks such as data augmentation, hyper-parameter tuning, and multi-layered architectures would be able to improve the classification performance. These findings highlight the capability of the ResNet50-based model in helping doctors with precise and effective brain tumor identification from MRI scans. Enhanced optimization techniques and access to a larger dataset could further improve the model’s effectiveness and utility in clinical applications.

Obtained Result

These results achieved are indicative of the success of the proposed brain tumor detection model from ResNet50 architecture. Interpretation of results entails examining the performance metrics of the model against its purposeful application. Critical findings and observations from the results are presented to offer insights into the strengths and weaknesses of the model. The model's performance was measured in terms of metrics such as F1-score, Recall, and Precision for discriminating between healthy and brain tumor patients. The F1-score of both classes approximated to 0.96, indicating high accuracy. The Recall and Precision were also comparable at a level of about 0.96. These values reflect the efficacy of the model in medical imaging analysis. Figure 4 shows the performance measures of a diagnostic model for two classes: healthy and brain tumor patients. The tested metrics are F1-score, Recall, and Precision is the performance metric of a machine learning model as it is being trained and validated across different epochs. The x-axis is used to plot epoch number (1 to 28), whereas the y-axis is used to plot metric values (0 to 1). The following are graphed:

1. *Training Loss (Blue Line):* It is very high at the start, then it drops very quickly and goes flat, showing good learning from the training data.

2. *Training Accuracy (Orange Line):* Goes up as the model learns, up to a high value.
3. *Validation Loss (Light Blue Dotted Line):* It fluctuates but generally goes down, showing how well the model generalizes to new data.
4. *Validation Accuracy (Yellow Line):* It rises with some fluctuation, reflecting the performance of the model on validation data.
5. *Learning Rate (Purple Dotted Line):* Does not change for all epochs, effecting optimization.

Comparison with Existing Approaches

A comparative study is there to compare the suggested model with the current methods of brain tumor detection in MRI images. Comparison helps to analyze the novelty and performance of the proposed methodology with respect to previous studies or baseline models. Salient differences, benefits, and limitations are outlined to situate the contribution of the suggested approach. Table 4 gives an extensive summary of existing work on brain tumor classification with CNN-based models, pointing out the datasets, CNN architectures, pre-processing methods, feature extraction techniques, classification types, and achieved accuracy results [19–23]. Gliomas, meningiomas, pituitary tumors, and normal/nontumor are some of the tumor cases addressed by the research presented in this Table 4. The dataset sizes range from a few hundred to more than 10,000 MRI images. To handle issues like class imbalance and improving image quality of inputs, pre-processing techniques like noise reduction, data augmentation, image scaling, and contrast stretching were usually used like wavelet transforms, discrete wavelet transforms (DWT), and Scale-Invariant Feature Transform (SIFT) [24–29]. Studies used methods such as transfer learning, leveraging pre-trained CNN models (e.g., Efficient Net, ResNet, Inception) for feature extraction. The classification included classifying certain tumor kinds (e.g., glioma, meningioma, pituitary) and their subcategories (e.g., benign, malignant).

The accuracies stated to differ with the model and dataset. Last but not least, indicates the evolution of CNN-based approaches to brain tumor classification and reflects numerous avenues to improve model performance, e.g., feature extraction techniques, pre-processing techniques, and classification models. The results show how using CNNs and state-of-the-art methods could improve the accuracy and reliability of brain tumor detection in medical images. In recent work on brain tumor detection from magnetic resonance images (MRI), various methods and deep architectures have been experimented to enhance accuracy and interpretability. One work compared transfer learning methods such as MobileNet, InceptionV3, ResNet50, and VGG19 using the BraTS 2015 dataset. Of all the models, ResNet50 proved to be the most effective one with the maximum accuracy of 95.42% [30–33]. Another study involved enhancing brain tumor detection with explainable artificial intelligence (AI) that merged ResNet50 with Gradient-weighted Class Activation Mapping (Grad-CAM). In rendering the explainability and transparency in tumor detection, this technique offered rich explanations of the model's predictions [14].

Table 4. Studies on brain tumor classification using convolutional neural networks (CNNs) with different pre-processing, feature extraction, and classification techniques.

Dataset Utilized	CNN Model	Types of Classification	Accuracy
3264 MRI images [19]	EfficientNetB7	Glioma, Meningioma, Pituitary, No Tumor	98.97%
3762 MRI images	EfficientNet-B0, MobileNet-V2, VGG-16, VGG-19	Glioma, Meningioma, Pituitary, No Tumor	98.67%, 92.6%, 93.9%, 97%
3064 MRI images [20]	VGGNet	Glioma, Pituitary, Meningioma	98.85%
2870 images [21]	Inception-v3, DenseNet201	Glioma, Meningioma, Pituitary, No Tumor	98.50%
4850 MRI Images [22]	CNN with KNN Classifier	Primary, No Tumor	99.54%
2577 MRI images [23]	Proposed ResNet50 (fine-tuned)	Binary Classification: Brain Tumor vs. Healthy	96.20%

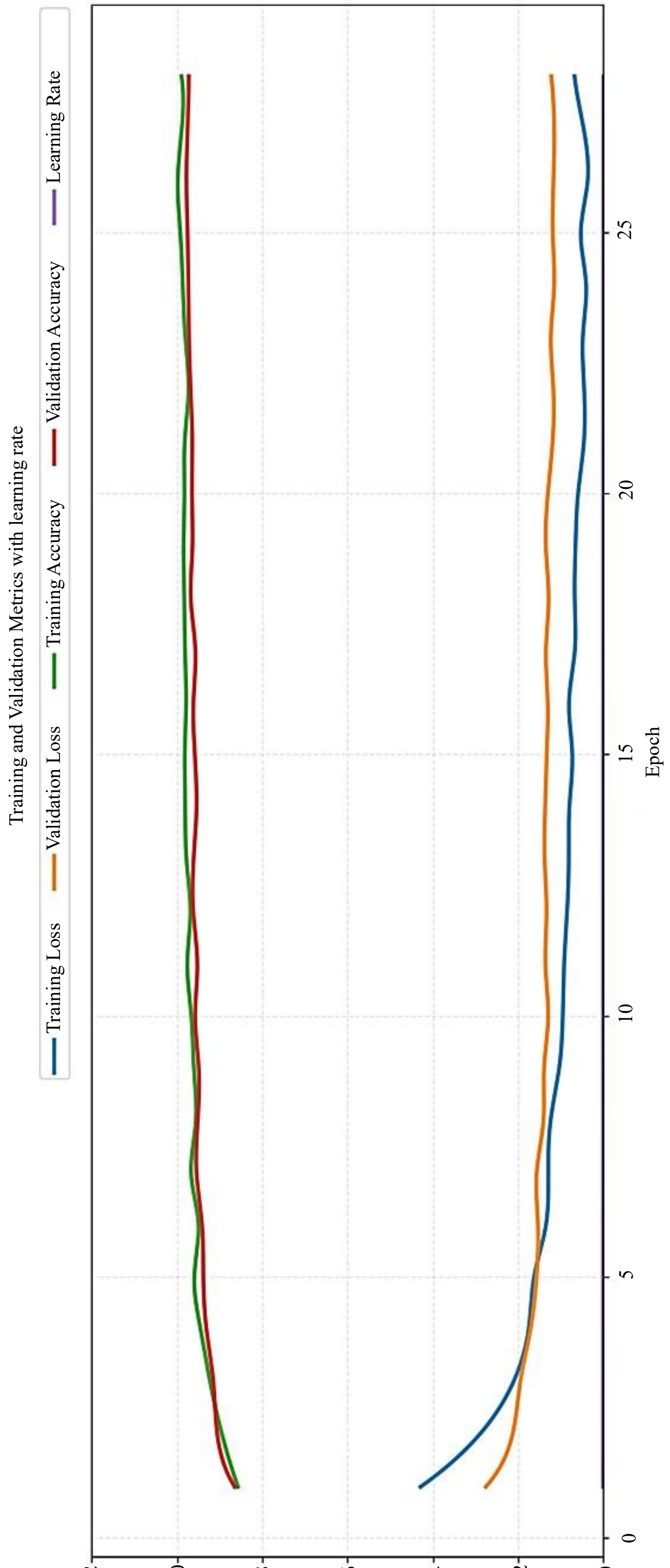

Figure 5. Training and validation with learning rate.

Another study proposed a better ResNet50 architecture developed to specifically identify intricate features in brain tumor images as shown in Figure 5. This design surpassed other models, such as AlexNet, GoogleNet, ResNet18, and ResNet50, on accuracy, sensitivity, specificity, and precision [34]. Another in-depth analysis of brain tumor detection using CNN also compared the ResNet-50, VGG16, and Inception V3 models. The proposed CNN architecture showed competitive performance, highlighting the robust effectiveness of ResNet50 in brain tumor detection tasks [35]. Precise identification of brain tumors from magnetic resonance images is vital for diagnosis and treatment. There have been some studies that have proposed advanced approaches for tumor detection, which were more accurate. Deep learning algorithms using CNNs and RNNs have shown higher sensitivity and specificity in detecting brain tumors using multimodal MRI data [36]. In addition, usage of ANFIS classifiers following Curvelet transform preprocessing has revealed good accuracy, sensitivity, and specificity in identifying meningioma tumors [37]. Further, the YOLOv7 neural network model has proven to be highly accurate in brain tumor diagnosis, which is automatic, and better than the older versions with a score of 94% [4]. In addition, machine learning algorithms using DCT feature maps have attained 95% testing accuracy in brain tumor detection from MRI scans [38, 39]. The progress showcases the promises of deep learning and machine learning strategies in enhancing the accuracy of brain tumor detection from magnetic resonance images. However, ResNet50 is an excellent choice for medical image-related applications because it is transparent, interpretable, and highly accurate. Scientists continue to study variations and improvements to further advance models of brain tumor classification to support diagnostic performance in the clinical environment.

CONCLUSION

The study proves the ability of the model based on ResNet50 in identifying brain tumors from MRI images. The accuracy of the test dataset is 97.35%, and the model is promising in differentiating between a normal brain image and an image of a brain tumor. Metric such as precision, recall, and F1-score represent the quality and reliability of the model. Confusion matrix and classification report provide further strong evidence to these results, reflecting the strong performance of the model under various criteria of evaluation. Great precision and stability of the model developed indicate tremendous potential for use in clinical environments. Through the availability of a trusted tool for the early and correct identification of brain tumors, the model would assist radiologists and clinicians at diagnosis, which may result in improved patient outcomes. Integrating such a model into clinical workflows would improve the efficiency of diagnostic processes, reduce the workload of radiologists, and facilitate timely medical intervention. Lastly, the resulting ResNet50-based model for MRI image brain tumor detection performs well and has excellent potential to apply to clinical scenarios. The performance is promising though, but limits and future breakthroughs in ways to make the model even better and more widely applicable need consideration. Ongoing R&D down this line matters for the establishment of medical image analysis and expanding diagnostic performance under clinical circumstances.

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