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Transfer Learning for MRI image reconstruction: Enhancing model performance with pretrained networks

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Abstract

These Neurologists and radiologists have the important responsibility of finding brain tumors early on. Brain tumor detection and segmentation using Magnetic Resonance Imaging (MRI) data is complex and error-prone when done manually. That is why an automated approach to detecting brain tumors is so important for early detection. This study introduces a new approach to brain tumor classification that makes use of DL and the MobileNet model. The Brain Tumor MRI Dataset follows preprocessing routines by resizing images along with converting them to grayscale before performing normalization. MobileNet implements depth-wise separable convolutions during training, which utilizes categorical cross-entropy loss for performance evaluation through accuracy, precision, recall and F1-score methods. EfficientNetV2-S reaches 99.23% accuracy while maintaining 99.42% precision, 99.34% recall, and 99.35% F1-score, which exceeds the performance of VGG19 (96%) and EfficientNetV2-S (96.19%). The model presents high precision (99.42%) and recall (99.34%) metrics, which support its ability to detect positive cases effectively. MobileNet demonstrates its value as both a trustworthy technology and efficient system for brain tumor diagnostic systems used in medical practice.

Keywords: Healthcare, Brain Tumor Detection; Medical Imaging; Computer-Aided Diagnosis (CAD); Deep Learning; Brain Tumor MRI Dataset

1. Introduction

The advancement of technology has led to better healthcare throughout recent years with exceptional impacts on disease identification and treatment and healthcare delivery to patients [1]. The early discovery of diseases makes critical contributions to patient survival chances as well as timely medical care provision. Complex and sometimes fatal brain-related illnesses, including brain tumors, are among the many medical ailments that pose serious dangers to public health [2]. Human life functions, intellect, and general physiological processes are all under the direction of the brain, the most complex organ in the body. However, it is also susceptible to various abnormalities, including tumors that can disrupt its normal operations. According to research, brain tumors account for the majority of cancer-related deaths among both children and adults worldwide [3]. A brain tumor is the most common brain disease. It is the process of brain cells developing uncontrollably. It is standard practice to distinguish between primary and secondary brain tumors [4]. The former often begins in the brain and does not spread, whereas the latter begins as cancer elsewhere in the body and eventually makes its way to the brain. Malignant and benign tumors are the two main categories of these growths. The difference between a malignant tumor, which aggressively spreads from one site to another, and a benign tumor is that the former grows slowly and does not invade neighboring tissues [5]. Grades I–IV are assigned to brain tumors by the WHO. Class I and II tumors often progress at a slower rate, whereas class III and IV tumors are almost always malignant and have an extremely poor prognosis [6]. Treatment planning and patient outcomes are greatly enhanced by early and accurate diagnosis of brain tumors.

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The accuracy and timeliness of a radiologist's identification of a brain tumor are major factors in the lengthy process [7]. Traditional methods are both expensive and inaccurate due to the exponential growth in patient data and the resulting explosion in the amount of data that needs processing. To get around the problems with manual diagnosis and similar applications, there has been a recent uptick in the interest in developing automated image processing technology. Automated brain tumor diagnosis has been made possible by a number of newly developed computer-aided diagnostic (CAD) systems [8]. In recent decades, various imaging techniques like X-ray, Computed Tomography (CT), Ultrasonography, Electroencephalography (EEG), and Magnetic Resonance Imaging (MRI) have been developed to enhance brain tumor diagnosis by providing detailed structural insights [9][10].

MRI has surpassed all others in producing high-resolution, non-invasive pictures without subjecting patients to ionizing radiation, making it the go-to method [11]. ML, a subset of AI, has gained significant attention in brain tumor detection, with researchers exploring various algorithms to enhance classification accuracy and minimize errors [12]. Specifically, DL approaches have been extensively used to build automated systems that can reliably segment and categorize brain tumors in a fraction of the time it used to, which greatly improved diagnostic efficiency and allowed for more prompt medical intervention [13].

1.1. Motivation and Contribution of Study

The motivation behind this study arises from the increasing demand for faster and more accurate MRI image reconstruction in medical diagnostics. Conventional MRI scanning techniques often suffer from long acquisition times, leading to motion artifacts and reduced clinical efficiency. There has been promising progress in DL, especially in transfer learning, that might greatly improve MRI image reconstruction in recent times. However, optimizing pre-trained models for this task remains an area of active research. This study aims to bridge the gap by leveraging transfer learning techniques with state-of-the-art DL models to enhance MRI reconstruction quality while reducing computational costs and time. The main advantages of this study are as follows:

- Utilization of a Brain Tumor MRI Dataset consisting of 7023 images for model training and evaluation.
- Enhances picture quality and streamlines model training by applying image scaling, greyscale conversion, and data normalization.
- Uses augmentation techniques to strengthen models and lessen the likelihood of overfitting, including rotating, scaling, and flipping.
- To improve computing economy while keeping classification accuracy high, it uses MobileNet's depth-wise separable convolutions.
- Model efficacy in classification tasks assessed using F1-score, recall, accuracy, and precision.

1.2. Structure of paper

The paper is organized as follows: The relevant literature on the categorization of brain tumors is reviewed in Section II. Section III outlines the methodology with model implementation. Section IV presents results and model comparisons, and future research directions are concluded in Section V.

2. Literature Review

This section reviews existing literature on MRI images for brain tumor detection. Most works focus on applying deep learning-based models to accelerate MRI reconstruction, improve image quality, and enhance diagnostic accuracy. Some of the reviewed works are:

Ravali, Chandra Shaker Reddy and Praveen (2024) A deep learning model based on federated learning that uses CNNs to automatically and accurately classify brain tumors in order to overcome these problems. By including pre-trained convolutional neural network (CNN), this model architecture takes advantage of the transfer learning technique. Overall, the model achieves 98.5% accuracy, demonstrating its effectiveness in diagnosing different types of tumors [14].

Siddiqua, Oni and Miah (2024) transfer learning has also shown promising outcomes in classifying neurological conditions using brain MRI data. Used dataset for the study has three classes; PD, Alzheimer's Disease (AD), and control (healthy). The research evaluates the CNN models under consideration by comparing their F1 scores, recall, accuracy, and precision. With a maximum accuracy of 99%, the EfficientNetB0 model clearly outperforms the competition in both training and testing [15].

Nizamli and Filatov (2024) present an enhanced transfer learning approach that aims to differentiate brain tumor types using MRI scans while achieving advanced performance. In the proposed approach, the pre-trained VGG-19 network with fixed weights is used to map MRI scans to a high-level numerical representation. For evaluation, the benchmark Figshare dataset containing 3064 MRI images was used after a series of processing operations. Outperforming its competitors, the suggested solution attained an impressive total accuracy of 98.53% [16].

Almufareh et al. (2024) a comparative analysis of YOLOv5 and YOLOv7 machine vision algorithms utilizing profound neural structures for the identification and classification of brain tumors with the help of MRI scans. A numerical outcome of YOLOv5 demonstrated that for mask segmentation, the re-call score was 0.905, and for box detection, the precision score was 0.936. At an IoU threshold of 0.5, both box detection and mask segmentation achieve mAPs of 0.947. However, when the IoU threshold is increased from 0.5 to 0.95, box detection reaches mAPs of 0.666 and mask segmentation reaches mAPs of 0.657. With an accuracy of 0.935 for mask segmentation and 0.936 for box recognition, YOLOv7 accomplishes remarkable performance outcomes. Box detection has a recall score of 0.904 and mask segmentation has a recall score of 0.903 [17].

Sathish, Kabekody and J (2023) have an effective means of detecting the deadly cancerous growth and, thus, starting therapy early. First, the MRI pictures are filtered using the Weiner filter, median, and cascading mean. The initial CNN achieved a 92.3% accuracy rate when comparing normal and abnormal brain MRI scans. When comparing HGG with LGG, the second CNN had a 98.4 percent accuracy rate [18].

The comparative analysis of background study based on their Author Name, Methodology, dataset, Key findings, Limitations, and Future work are provided in Table I.

Table 1 Comparative Analysis of background study on brain tumor detection MRI Image Classification

Author(s)	Methodology	Dataset	Key Findings	Limitations	Future Work
Ravali, Chandra Shaker Reddy & Praveen (2024)	Federated Learning with modified VGG16. Uses transfer learning with pre-trained CNN to classify brain tumors.	Brain MRI dataset collected from multiple institutions to ensure diversity.	Achieved 98.5% accuracy in brain tumor classification using pre-trained CNN. Improved feature extraction enhances diagnosis accuracy.	Limited to brain tumor classification. Requires more validation on unseen datasets.	Expansion to other neurological conditions, improving federated learning efficiency, and testing on real-world clinical data.
Siddiqua, Oni & Miah (2024)	Transfer learning with CNN architectures (EfficientNetB0, ResNet50, InceptionV3, Xception). Performance evaluated on multiple metrics.	Brain MRI dataset consists of three classes: Parkinson's disease (PD), AD, and control (healthy).	EfficientNetB0 achieved the highest accuracy of 99%. Comparison of different CNN models provides insight into the best architecture for neurological classification.	Limited dataset diversity. May not generalize well to new cases.	Evaluation on larger, more diverse datasets. Integrating explainable AI techniques to enhance model interpretability.
Nizamli & Filatov (2024)	VGG-19 with SVM and feature optimization (L1-penalty, radial basis similarity function). Uses transfer learning to map MRI images to numerical representations.	Figshare dataset containing 3064 MRI images of different tumor types.	Achieved 98.53% accuracy, outperforming previous models. Feature optimization significantly improves classification accuracy.	Requires high computational resources. Potential overfitting on limited datasets.	Investigate alternative feature selection methods. Reduce computational complexity to enhance real-world applicability.

Almufareh et al. (2024)	YOLOv5 and YOLOv7 for brain tumor detection. Uses deep learning-based object detection for improved accuracy.	Brain tumor dataset contains three classes: Meningioma, Glioma, and Pituitary tumors.	YOLOv7 achieved better accuracy and precision in detection. Box detection and mask segmentation achieved high mAP scores.	Dependence on preprocessing techniques. Requires extensive labeled data for training.	Improving detection in complex cases. Expanding the dataset to encompass a wider range of tumor types and conducting tests on clinical MRI images.
Sathish, Kabekody & J (2023)	Image preprocessing with cascading mean, median, and Weiner filters. CNN-based classification after ROI extraction.	MRI brain tumor dataset containing Low-Grade Glioma (LGG) and High-Grade Glioma (HGG).	98.4% accuracy in distinguishing HGG from LGG. Effective tumor region extraction and classification.	Skull artifacts impact accuracy. Preprocessing techniques may introduce errors.	Addressing segmentation errors with improved skull stripping. Testing on more datasets with various MRI machines.

3. Methodology

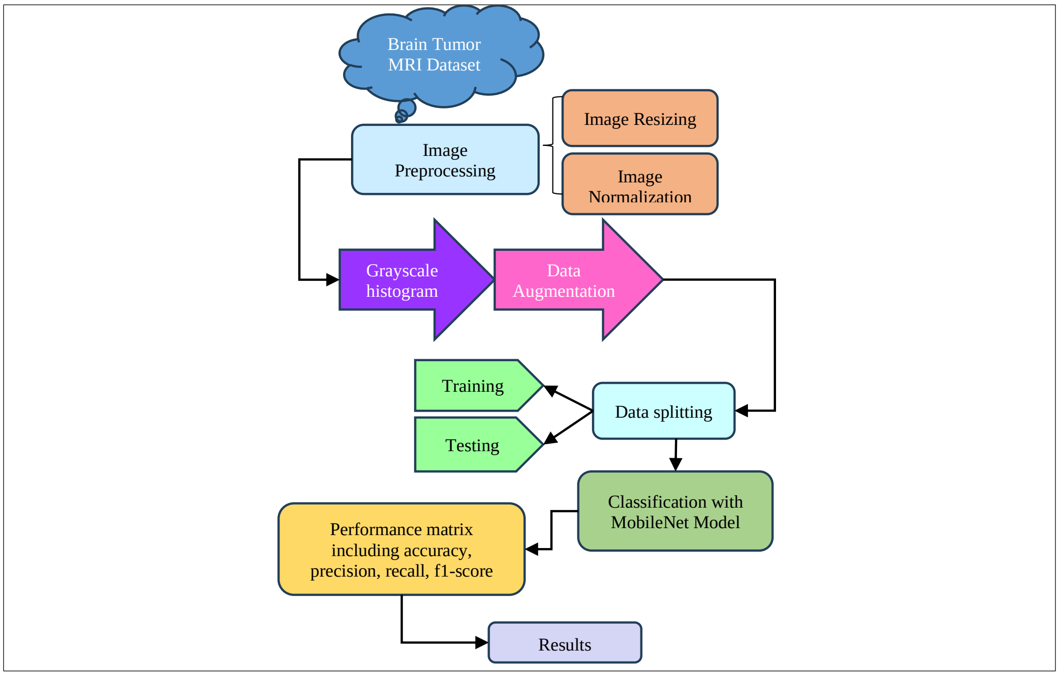

Figure 1 Flowchart of the Brain Tumor MRI Classification

There are a number of critical elements in the process that guarantee efficient and accurate model performance when classifying brain tumors employing MRI data. The Brain Tumor MRI Dataset, which consists of 7023 pictures classified as pituitary tumor, meningioma, glioma, and no tumor, is preprocessed using grayscale conversion, data normalization, and image scaling (224x224 pixels) to normalize pixel values for better model training. Data augmentation methods, such scaling and rotation, improve the generalizability of models. Twenty percent of the data is kept aside for testing purposes, while eighty percent is used for training. Classification and feature extraction are carried out via the MobileNet model, which makes use of depth-wise separable convolutions. Feature extraction is handled by convolutional layers, representation training by flattening and fully connected layers, and multi-class classification by a final SoftMax activation layer. A 0.5 dropout layer is used to avoid overfitting. It uses categorical cross-entropy loss for training and optimization and measures the model's performance with F1-score, recall, accuracy, and precision. This approach ensures robust classification performance and aids in effective brain tumor diagnosis. The following steps of the research design are displayed in Figure 1 flowchart.

The overall steps of the flowchart for MRI Image Classification are provided below:

3.1. Data Collection

This research study uses the publicly accessible Brain Tumor MRI Dataset. The 7023 photos in this collection include 2000 images without tumors, 1757 images with pituitary tumors, 1621 images with gliomas, and 1645 images with meningiomas. It is visually represented as:

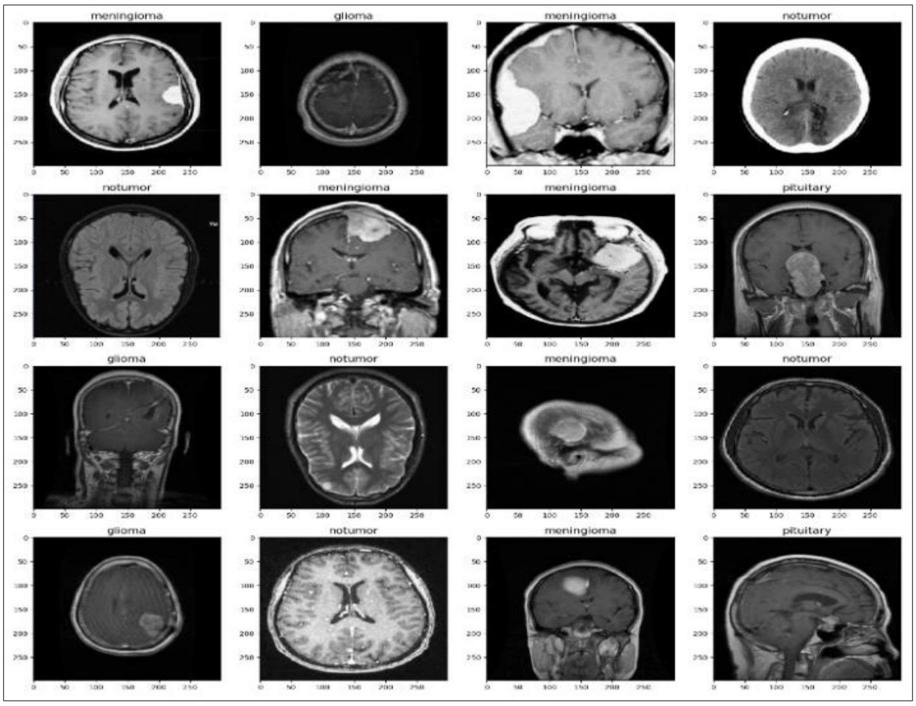

Figure 2 Brain MRI Data Sample

Figure 2 presents a sample of brain MRI scans categorized into glioma, meningioma, pituitary tumor, and no tumor (healthy brain) conditions. Images captured in different orientations (axial, coronal, and sagittal) highlight tumor variations in structure and location.

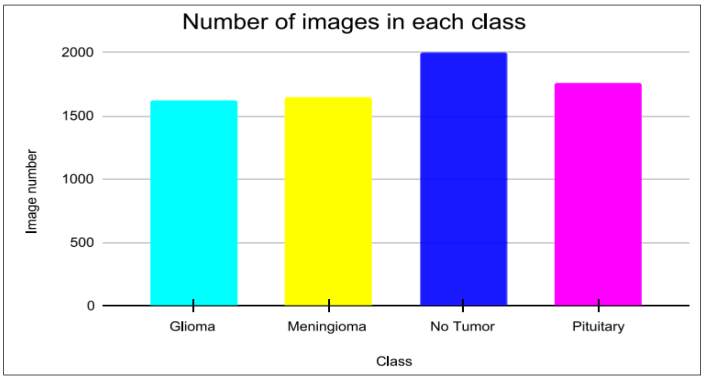

Figure 3 Bar Graph for Tumor classes

Figure 3, bar graph illustrates the distribution of image classes, showcasing the number of images within each category. "No Tumor" exhibits the highest count, reaching approximately 2000 images. "Glioma" and "Meningioma" classes contain roughly 1600 images each, while "Pituitary" has around 1750, highlighting variations in dataset representation [19].

Figure 4, pie chart displays the distribution of four categories: Glioma, Pituitary, No Tumor, and Meningioma, represented by red, yellow, blue, and green slices, respectively. Each slice indicates the number of items and their percentage. Meningioma has the highest count (937, 28.7%), followed by Glioma (926, 28.4%), Pituitary (901, 27.6%), and No Tumor with the lowest (500, 15.3%).

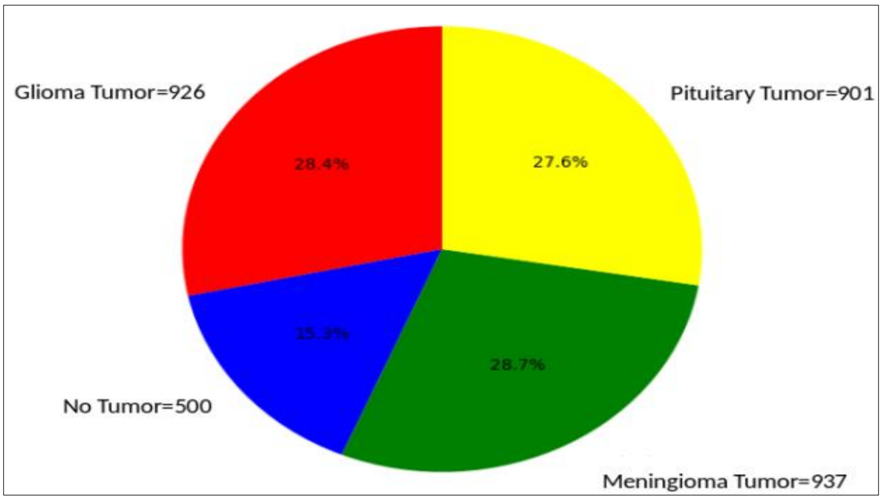

Figure 4 Pie chart for Brain tumor distribution

3.2. Image Preprocessing

An important part of using MRI and other medical imaging methods to diagnose brain tumors is picture preprocessing. [20] Accurate interpretation and analysis by medical specialists may be achieved by image preprocessing, which entails a series of processes carried out on raw picture data to improve image quality, decrease noise, and extract important characteristics. The following pre-processing steps are listed below:

3.2.1. Image Resizing: In this step, all images are resized into 224 by 224 pixels.

Image Normalization: Image normalization is a preprocessing technique utilized in computer vision to scale pixel values to a standard range, typically [0,1] or [-1,1], to improve model performance and training stability. By normalizing images, variations in lighting, contrast, and intensity are minimized, ensuring that neural networks learn features effectively without being biased by absolute pixel values.

3.3. Grayscale Conversion

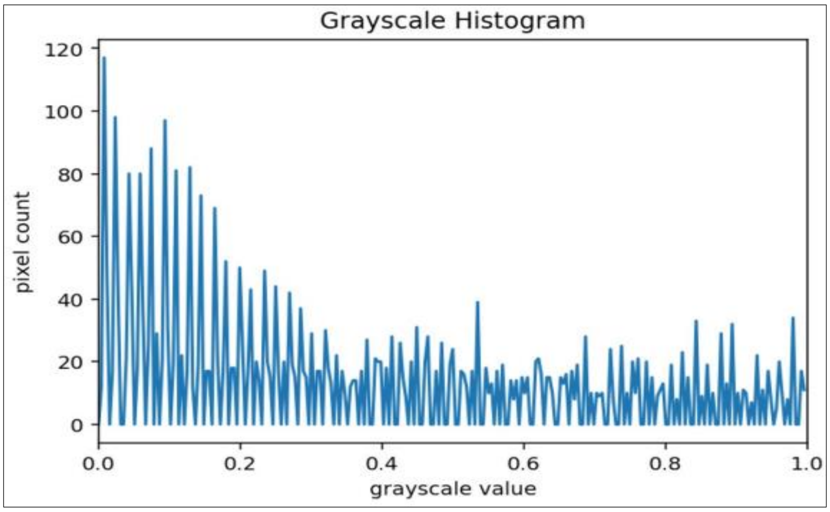

Figure 5 Grayscale Histogram

Grayscale conversion simplifies MRI image processing by transforming color images into intensity-based representations. This reduces computational complexity while preserving important structural details, enhancing feature extraction, and improving classification accuracy.

Figure 5, The grayscale histogram displays the distribution of pixel intensities in an image, ranging from 0 (black) to 1 (white). The higher concentration of pixel values near 0 suggests that the image is predominantly dark. The decreasing frequency of higher intensity values indicates fewer bright regions, contributing to an overall darker visual composition.

3.4. Data Augmentation

The process of applying several alteration techniques to actual photographs to create modified copies of the same picture is known as image augmentation. Picture augmentation is done using the Image Data Generator class. As a whole, the mode is more robust and accurate, and it can automatically generate improved images while training the model. Data augmentation can be mathematically represented as Equation (1):

$$X' = T(X, \theta) \qquad \ldots\ldots\ldots\ldots(1)$$

where X is the original data (such as an image, text, or numerical dataset), X′ is the augmented data, T is a transformation function, and θ represents transformation parameters like Rotation Angle, Scaling Factor, and translation values, which modify the original data to create diverse variations for improving model generalization.

3.4.1. Data Splitting

Split the dataset in half, using 80% for training and 20% for testing. A training set was utilized to fine-tune and train the models before they were tested on the testing set.

Classification with MobileNet Model

The MobileNet model is based on a novel sort of convolution layer called depth-wise separable convolution. It is a neural network model. Layers one and two of its depth-wise separable convolution are point convolution and layer three is the depth-wise convolution [21][22]. The point convolution filter uses $1 * 1$ convolutions to linearly aggregate the output of the depth-wise convolution filter, with each input channel passing through one convolution via the former. A feature map is created by applying a tiny array of integers (the kernel) over the input picture via convolution, a linear technique for feature extraction. The flatten layer takes this map and makes it an array with just one dimension. The fully connected layer follows, where the flattened output is fed into multiple neurons—typically 128 with a ReLU activation function. It is possible to activate a single neuron using "ReLU" as shown in Equation (2):

$$h_\theta(x) = ReLU(w^T x + b), where\ w \in R^d, b \in R, and \theta = \qquad (w, b) \ldots\ldots(2)$$

where “b” is a bias and “w” is a weight. The fourth layer's output is passed on to the fifth layer. Overfitting may be avoided by using the fifth layer, which is called the dropout layer. Research has shown that big neural networks perform best with a dropout rate of half. Next, the output layer takes the output from the dropout layer as its input. Because the model may make predictions for three different kinds of things, this layer uses three neurons. Equation (3) shows that the output layer uses the activation function called "SoftMax":

$$p\left(y = j | \Theta^{(i)}\right) = \frac{e^{\Theta^{(i)}}}{\sum_{j=0}^{k} e^{\Theta_k^{(i)}}} \qquad \ldots\ldots\ldots\ldots(3)$$

where $\Theta = w^T x$ is the sum of scores and “i” is the input parameter [23]. The SoftMax activation function assigns a decimal probability to each label class, with a total of one as the result.

Performance Matrix

Performance metrics are utilized to evaluate an effectiveness of a classification model. It helps determine how well a model can predict both positive and negative instances. The measures utilized to assess the performance of several models on the test set were accuracy, F1 score, precision, recall, and average loss. All of these measures are appropriate for categorization tasks. All the equations can be found as follows:

- True Positive (TP): The presence of the clinical anomaly is indicated by a positive test result.
- True Negative (TN): The absence of any clinical problems is signified by a negative test result.
- False Positive (FP): Without the presence of the clinical anomaly, the test comes out positive.
- False Negative (FN): Despite the existence of the clinical anomaly, the test comes out negative.

Accuracy

Accuracy, which is based on the ratio of expected correct outcomes to actual observations, is the most often used statistical measure, as per the Equation (4) given below:

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad \ldots\ldots\ldots\ldots(4)$$

Recall

The accuracy rate of positive predictions relative to all other actual values is called recall. As seen, it is Equation (5):

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad \ldots\ldots\ldots\ldots\ldots(5)$$

Precision

The percentage of correctly anticipated positive values among all projected positive values is known as precision. It may be shown graphically in Equation (6):

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad \ldots\ldots\ldots\ldots\ldots(6)$$

F1 Score

The F1-score is a harmonic mean of the recall and precision scores; it is a measure of performance for classification problems. Equation (7) is a common way to depict it:

$$\text{F1} = \frac{2*(\text{precision}*\text{recall})}{\text{precision+recall}} \quad \ldots\ldots\ldots(7)$$

Loss: The loss metric quantifies the dispersion between the actual values and the predictions made by a model. It quantifies the error during training and is used to update model parameters.

4. Results and Discussion

The data was processed and analyzed using the TensorFlow backend in Python 3. It ran the reconstruction techniques on a 64-bit Windows 10 Pro workstation with an Intel i7 CPU (3.60 GHz, four-core), 16 GB RAM, and an NVIDIA GV100GL GPU. This section showcases the suggested model's performance on several metrics from the performance matrix, like recall, accuracy, precision, and f1score. Table II displays the findings of the MobileNet model for the Brain Tumor MRI dataset.

Table 2 Performance Evaluation of MobileNet Model for MRI Image Classification

Performance Matrix	MobileNet
Accuracy	99.23
Precision	99.42
Recall	99.34
F1 score	99.35

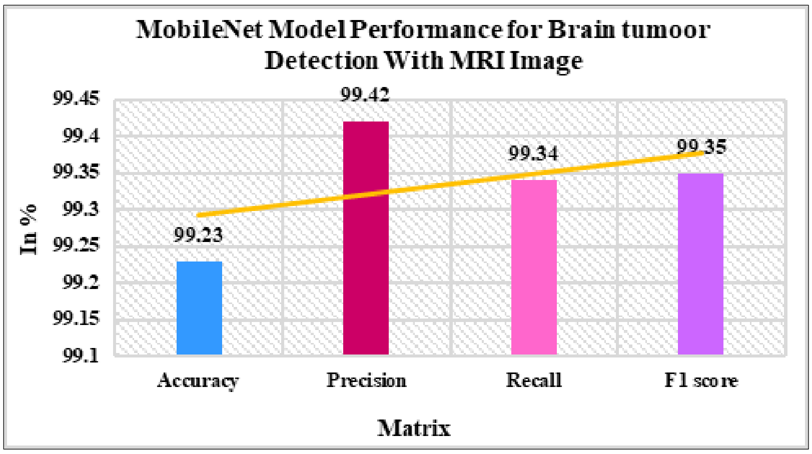

Figure 6 Bar Graph for MobileNet Model Performance

This section presents performance results from the MobileNet model's operation as an MRI image classifier through Table II and Figure 6. The model achieves 99.23% accuracy in its consistent MRI classification performance. The model demonstrates 99.34% accuracy in positive image identification together with 99.42% precision which reduces false positive results. The MobileNet model displays excellent performance for MRI image classification through its F1-score value of 99.35% which demonstrates perfect precision-recall balance.

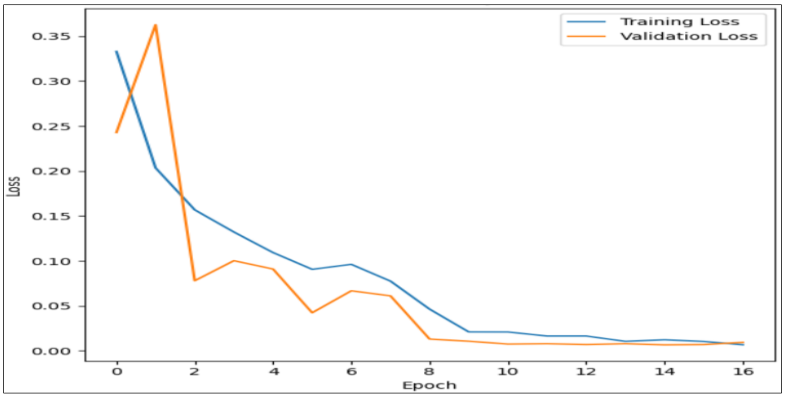

Figure 7 Loss curve for MobileNet model

Figure 7, displayed the training and validation loss of a model over 16 epochs. Both losses rapidly decrease initially, indicating effective learning. The validation loss exhibits variations that might indicate model overfitting or a high sensitivity to validation data entries. A successful model training combined with generalization occurs when both losses reach a low-end point.

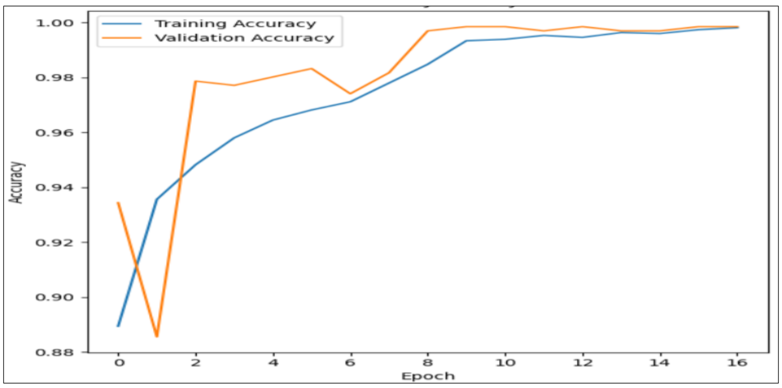

Figure 8 Accuracy curve for MobileNet model

Figure 8 shows that a model's training and validation accuracy path takes place over the period of sixteen epochs. The accuracy rates experience quick growth in their initial stage which demonstrates proper learning occurs. The validation accuracy shows several ups and downs which can indicate overfitting has occurred. The model training successfully progresses as both accuracy values reach equivalent values of approximately 1.00.

4.1. Comparative Analysis

This section evaluates an application of different DL models for MRI image reconstruction together with classification tasks. Table III utilizes the performance assessment measures of accuracy, precision, recall and F1-score to evaluate VGG19, EfficientNetV2-S and MobileNet.

Table 3 Comparison of Deep Learning Models for MRI-Based Brain Tumor Classification

Performance Metric	VGG19 [24]	EfficientNetV2-S [25]	MobileNet Model
Accuracy	96	96.19	99.23
Precision	93	-	99.42
Recall	93	-	99.34
F1 score	93	96.29	99.35

MobileNet delivers superior results in brain tumor classification tasks when compared to MRI-based tests performed by VGG19 and EfficientNetV2-S models as demonstrated in Table III. The accuracy rate of 99.23% established MobileNet as a superior performer than VGG19 (96%) and EfficientNetV2-S (96.19%) for MRI-based brain tumor classification.

Results from using MobileNet-based methodology to classify brain tumors outperform those from using traditional deep learning techniques. Depth-wise separable convolutions let the model achieve its efficient design to reduce processing complexity while maintaining classification accuracy. The model functions with 99.23% accuracy, which surpasses both VGG19 and EfficientNetV2-S, thus proving its ability to handle MRI dataset generalization tasks. MobileNet serves as a superior solution for real-time clinical usage because of its many advantages which work best in resource-limited environments.

5. Conclusion

MRI scans have recently demonstrated their use in the study of brain tumor detection and segmentation. According to MRI scans, the brain tumor could be found. Abnormal tissue development or blood blockages are seen by the neurological system in the MRI image. The symmetry and asymmetry of the brain's structure are used to detect anomalies, and controlling them is the first step in identifying a brain tumor. The research shows that the MobileNet model is superior to VGG19 and EfficientNetV2-S for classifying brain tumors from MRI scans, with an accuracy of 99.23%. The study demonstrates that the model maintains stability in extracting features and performing classifications which makes it suitable for automated tumor detection systems. However, limitations include potential overfitting due to dataset constraints and sensitivity to variations in MRI acquisition parameters. Additionally, the study does not incorporate multimodal imaging data or advanced ensemble strategies, which could further enhance performance. Future research should explore larger and more diverse datasets, hybrid deep learning models, and attention-based mechanisms to improve interpretability and clinical applicability in real-world scenarios. “

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