

Enhanced Brain Tumor Classification using Optimized AlexNet CNN Model with Hyperparameter Tuning

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Abstract—Brain tumors are a leading cause of disability and mortality worldwide, making their timely and accurate detection essential for improving patient survival and quality of life. This study explores the influence of hyperparameter tuning on the performance of Convolutional Neural Networks (CNNs) in brain tumor classification using a dataset of 7023 MRI images categorized into pituitary, glioma, meningioma, and no tumor. Leveraging a tailored AlexNet architecture, the model was trained with varying epochs (10, 15, and 20), a batch size of 32, and the Adamax optimizer with a learning rate of 0.001. The optimized model achieved a training accuracy of 99.31% and an AUC of 0.9999, with a validation accuracy of 96.15% and an AUC of 0.9973. On the test set, it demonstrated a classification accuracy of 98%. Metrics such as F-measure, ROC, precision, recall, and accuracy underscore the robustness of this approach in enhancing brain tumor detection.

Index Terms—Brain Tumor, Convolution Neural Network, Hyper-tuned Parameter, MRI Dataset.

I. INTRODUCTION

In the realm of medical imaging, the quest for precise and timely diagnosis of brain tumors has long been a cornerstone in the battle against neurological disorders. Among the various imaging modalities available, magnetic resonance imaging (MRI) is a powerful tool for capturing detailed anatomical information with unparalleled clarity [1]. Over the years, the integration of advanced computational methodologies, particularly deep learning techniques, has revolutionized the field of medical image analysis, offering new avenues for enhancing the accuracy and efficiency of tumor detection and classification [2]. Gliomas, originating from glial cells, represent the most common type of primary brain tumors. Pituitary tumors, can exert significant physiological and neurological effects due to their proximity to critical structures within the brain. The accurate delineation and characterization of these tumors are paramount for guiding treatment strategies and optimizing patient care [3], [4]. The deep learning techniques can automatically learn complex patterns from large datasets of MRI images, enabling them to detect brain tumors with high accuracy [5]. The primary objective of this study is to investigate the application of deep learning techniques for detecting and classifying brain tumors, with a specific focus on four prevalent types: gliomas, pituitary tumors, and healthy brain tissue, using MRI images. By leveraging the power of convolutional neural networks (CNNs), the aim is to develop robust and reliable algorithms capable of accurately identifying tumor regions [6].

Neurological disorders such as strokes, brain hemorrhages, multiple sclerosis, and brain tumors pose significant challenges to patients and healthcare professionals alike. The timely and accurate diagnosis of these conditions is critical for initiating appropriate treatment and improving patient outcomes. Magnetic Resonance Imaging (MRI) scans are the gold standard for diagnosing brain tumors [7], [8]. Despite remarkable advancements in imaging technology and diagnostic methodologies, the detection and classification of brain tumors, particularly gliomas and pituitary tumors, remain challenging tasks fraught with inherent complexities.

This paper is organized as follows: Section 2 provides a comprehensive overview of brain tumor classification using deep learning techniques. Section 3 outlines the methodology employed in this work. Section 4 presents the recommended deep learning model's experimental results and performance evaluation. Finally, Section 5 concludes the work.

II. RELATED WORK

Early and accurate detection of brain tumors is crucial for improving patient outcomes, as timely interventions can substantially increase survival rates and quality of life. Conventional diagnostic methods, primarily reliant on manual inspection of medical imaging data, are both time-consuming and prone to human error. Consequently, there is a growing interest in leveraging advanced machine learning techniques, particularly Convolutional Neural Networks (CNNs), to enhance the accuracy and efficiency of brain tumor detection [9]. The AlexNet model achieved innovative success in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), highlighting the potential of deep learning models in addressing complex image recognition tasks [10]. The application of AlexNet and other CNN architectures in brain tumor detection has been explored extensively in recent literature. These studies highlight the efficacy of CNNs in automatically extracting and learning hierarchical features from medical images, thereby facilitating more accurate and automated tumor detection [11]. For instance, the potential of a CNN-based approach for segmenting tumor diseases from MRI images is demonstrated in [12], achieving remarkable segmentation accuracy. Similarly, the application of deep learning techniques, particularly Convolutional Neural Networks (CNNs), has significantly advanced medical image analysis. For instance, CNN-based methods have demonstrated remarkable accuracy in segmenting gliomas from MRI scans [13]. Furthermore, deep learning models have been effectively utilized to differentiate between various types of brain tumors, underscoring the versatility of CNNs in medical diagnostics [14]. The adaptation of AlexNet for brain tumor detection involves fine-tuning the model to address the specific characteristics of medical imaging data. This process typically includes modifying the network architecture, employing transfer learning techniques, and integrating domain-specific pre-processing steps [15]. Moreover, the combination of AlexNet with other CNN architectures, such as VGGNet, ResNet, and InceptionNet, has been investigated to enhance detection performance through ensemble method [16]. Despite the promising results, challenges remain in developing robust and generalizable models for brain tumor detection [17].

III. METHODOLOGY

Figure 1 shows the major steps involved in this work.



Figure 1. Methodology of the Work

A. Brain Tumor MRI dataset

The MRI image dataset utilized in this research was sourced from Kaggle, amalgamating three distinct repositories: Figshare, SARTAJ dataset, and Br35H. This comprehensive dataset comprises 7023 human brain MRI scans images, classified into four distinct classes: glioma, meningioma, no tumor, and pituitary. This dataset contains 2 folders: Training and Testing. Each folder has four sub-folders: glioma, meningioma, no tumor, and pituitary. Total MRI Images = 7023 [18]. Figure 2 shows some sample images of the brain tumor MRI dataset. The description of each class of the dataset is given in Table I.

B. Data preprocessing

The preprocessing pipeline involved the following steps:

Image Resizing: All images were resized to a uniform dimension of 240x240X3 pixels to ensure consistency across the dataset. The preprocessed dataset was partitioned into three distinct subsets: training, validation, and testing, following a standard ratio scheme. Approximately 80% of the total images were allocated to the training set, while the remaining 10% each were designated for the validation and testing sets.

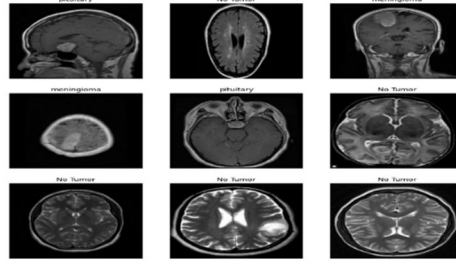


Figure 2. Brain Tumor MRI Dataset Sample

TABLE I. DESCRIPTION OVERVIEW OF BRAIN TUMOR MRI DATASET

S. No.	Sub-class	No. of samples	Description
1.	Glioma	1621	Affected
2.	Meningioma	1757	Affected
3.	Pituitary	1645	Affected
4.	No Tumor	2000	Normal

C. Model Training and Validation

The AlexNet architecture, a seminal convolutional neural network (CNN) model renowned for its efficacy in image classification tasks, was employed as the primary model for this study. Training was conducted over a predefined number of epochs, with early stopping mechanisms implemented to prevent overfitting. Throughout the training process, the performance of the AlexNet model was regularly validated using the validation dataset. Validation metrics such as accuracy, precision, recall, and area under the receiver operating characteristic curve (AUC-ROC) were computed to assess the model's generalization capabilities and identify potential areas for improvement. Upon completion of training and validation, the final performance evaluation of the AlexNet model was conducted using the independent testing dataset.

D. Training Configuration

The AlexNet model was trained using a comprehensive configuration scheme tailored to optimize performance and convergence. Specifically, the training regimen comprised 10, 15 and 20 epochs with a batch size of 32 samples per iteration. The Adamax optimizer was employed, with a learning rate of 0.001, to adjust the model weights during training dynamically. Rectified Linear Unit (ReLU) activation functions were utilized in both input and hidden layers to introduce non-linearity and enhance model expressiveness. Furthermore, the output layer was equipped with a softmax activation function to facilitate probabilistic interpretation of class predictions. Given an input image I and a filter/kernel K , the 2D convolution operation can be represented mathematically as follows:

$$C(i, j) = (I * K)(i, j) = \sum_m \sum_n I(m, n) \cdot K(i - m, j - n) \quad (1)$$

Where: $C(i, j)$ is the value at position (i, j) in the output feature map. $I(m, n)$ is the pixel value of the input image at position (m, n) . $K(i - m, j - n)$ is the value of the filter/kernel at position $(i - m, j - n)$. The double summation is performed over all valid positions of the filter/kernel in the input image. '*' denotes the convolution operation.

ReLU and Softmax are commonly used activation functions in convolutional neural networks (CNNs). ReLU is a simple non-linear activation function defined as:

$$ReLU(x) = \max(0, x) \quad (2)$$

The derivative of ReLU is 1 for positive inputs and 0 for negative inputs.

Softmax is used in the output layer of a neural network for multi-class classification problems. Given an input vector z with K elements (where K is the number of classes), the Softmax function is defined as:

$$\text{Softmax}(z)_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (3)$$

Where: $\text{Softmax}(z)_i$ is the i -th element of the output probability vector. e is Euler's number (approximately 2.71828). z_i is the i -th element of the input vector.

E. AlexNet Architecture Layers

It has one input layer, five convolutional layers, three Maxpool layers, two fully connected hidden layers and one output layer. Figure 3 shows the architecture of AlexNet model.

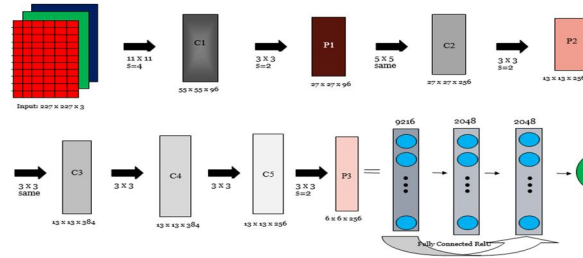


Figure 3. Architecture of AlexNet Model: C1, C2, C3, C4 and C5 are the Convolutional Layers. P1, P2, and P3 are the Maximum Pooling. 's' indicates strides

F. Hyper-parameter (Fine-Tuning) used in the AlexNet Model

Fine-tuning AlexNet to classify brain tumors involves the following steps: The process generally includes preparing a dataset, modifying the AlexNet architecture to suit a specific problem, and then training the model. Figure 4 shows the AlexNet model with fine-tuning and hyperparameters. The hyperparameter optimization used for this training is reported in Table II. Two key strategies were employed to mitigate the risk of overfitting and ensure optimal convergence: early stopping and learning rate reduction on the plateau. Early stopping was implemented with a patience parameter set to 3 epochs, monitoring validation accuracy for signs of stagnation or deterioration.

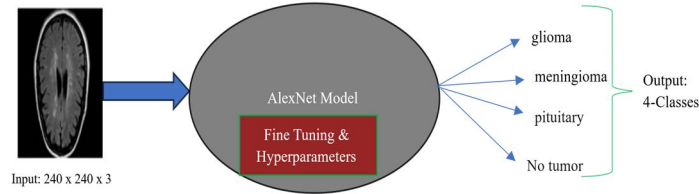


Figure 4. AlexNet model for the classification of brain tumor disease

TABLE II. OPTIMIZATION OF FINE-TUNED (HYPER-PARAMETERS) USED IN THIS WORK

Model	Hyper-parameters	Setting/value
CNN-AlexNet	Loss function	categorical_crossentropy
	Optimizer function	Adamax
	Metrics	Train and Test Loss, AUC, Accuracy
	Epochs	10, 15 and 20
	Batch size	32
	Learning rate	0.001

G. Performance Metrics

Key performance metrics included Accuracy, Precision, and Recall as discussed below.

Accuracy: The proportion of correctly classified instances out of the total dataset.

$$\text{Accuracy} = \frac{\text{TruePositive} + \text{TrueNegative}}{\text{TruePositive} + \text{TrueNegative} + \text{FalsePositive} + \text{FalseNegative}} \quad (4)$$

Precision: The ratio of true positive predictions to the total number of positive predictions, measuring the model's ability to avoid false positives.

$$\text{Precision} = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalsePositive}} \quad (5)$$

Recall: The ratio of true positive predictions to the total number of positive instances, quantifying the model's ability to capture relevant instances.

$$Recall = \frac{TruePositive}{TruePositive+FalseNegative} \quad (6)$$

F1-Score: The F1-score is the harmonic mean of precision and recall. It provides a single score that considers both false positives and false negatives. The formula for the F1-score is:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (7)$$

Loss: The measure of discrepancy between predicted and actual class labels, computed using appropriate loss functions such as categorical cross-entropy loss L. L is calculated as follows:

$$Loss = -\sum_{i=1}^c y_i * \log[\hat{y}_i] \quad (8)$$

Where: c is the number of classes, y_i is the actual probability that belongs to class i and $\hat{y}_i$ is the predicted probability that belongs to class i

True Positive Rate (TPR) or Sensitivity: Plotted on the y-axis, this is the proportion of actual positives that are correctly identified (i.e., how many tumors are correctly identified by the model).

$$TPR = \frac{TruePositive}{(TruePositive+FalseNegative)} \quad (9)$$

False Positive Rate (FPR): Plotted on the x-axis, this is the proportion of actual negatives that are incorrectly identified as positive (i.e., how many non-tumor cases are falsely classified as tumors).

$$FPR = \frac{FalsePositive}{(FalsePositive+TrueNegative)} \quad (10)$$

The ROC Curve: It shows the trade-off between the TPR and FPR.

IV. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

The experimental results highlight the AlexNet model's strong efficacy and robustness in classifying brain tumors from MRI images. The model effectively captures complex patterns by achieving a training accuracy of 99.97% and a training AUC of 1.0. Table III summarizes the average train/test loss, accuracy, and AUC scores across various epochs, while Table IV presents precision, recall, and F1 scores at epochs 10, 15, and 20. Figure 5 visualizes these metrics for all four tumor types, with and without augmentation. The model's ability to generalize and detect subtle tumor variations is evident in its test accuracy of 96.15% and test AUC of 0.9975, showcasing consistent performance improvements over time.

TABLE III. TRAIN AND TEST LOSS, ACCURACY, AUC AT DIFFERENT EPOCHS, BATCH SIZE = 32

Epoch = 10	Epoch = 15	Epoch = 20
Train Loss: 0.0338	Train Loss: 0.0070	Train Loss: 0.0067
Train Accuracy: 99.27%	Train Accuracy: 99.96%	Train Accuracy: 99.89%
Train AUC: 99.97%	Train AUC: 100.00%	Train AUC: 100.00%
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Test Loss: 0.1586	Test Loss: 0.1116	Test Loss: 0.1051
Test Accuracy: 94.72%	Test Accuracy: 97.72%	Test Accuracy: 97.72%
Test AUC: 99.34%	Test AUC: 99.47%	Test AUC: 99.65%%

TABLE IV. THE RESULTS OBTAINED USING THE ALEXNET MODEL ON BRAIN MRI DATASET AT DIFFERENT EPOCHS

Class	Precision	Recall	F1-Score	Avg. Accuracy
Epoch = 10				
glioma	0.94	0.94	0.94	0.9472
meningioma	0.92	0.88	0.90	
No Tumor	0.96	0.97	0.97	
pituitary	0.96	0.98	0.97	
Epoch = 15				
glioma	0.97	0.98	0.97	0.9772
meningioma	0.97	0.95	0.96	
No Tumor	0.99	0.99	0.99	
pituitary	0.98	0.99	0.98	

	Epoch = 20			
glioma	0.98	0.97	0.98	0.9772
meningioma	0.98	0.96	0.97	
No Tumor	0.99	0.99	0.99	
pituitary	0.97	0.98	0.97	

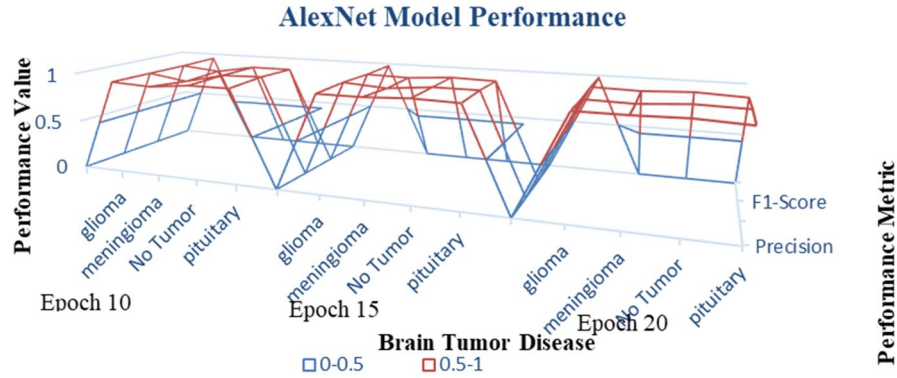


Figure 5. Performance graph of Brain Tumor Disease using Hype-tuned AlexNet Model without Augmentation

The graphical representation of the training progress of the hyper-tuned AlexNet model is shown in Figure 6. This figure presents four plots depicting the training and validation metrics for the model across 10, 15, and 20 epochs.

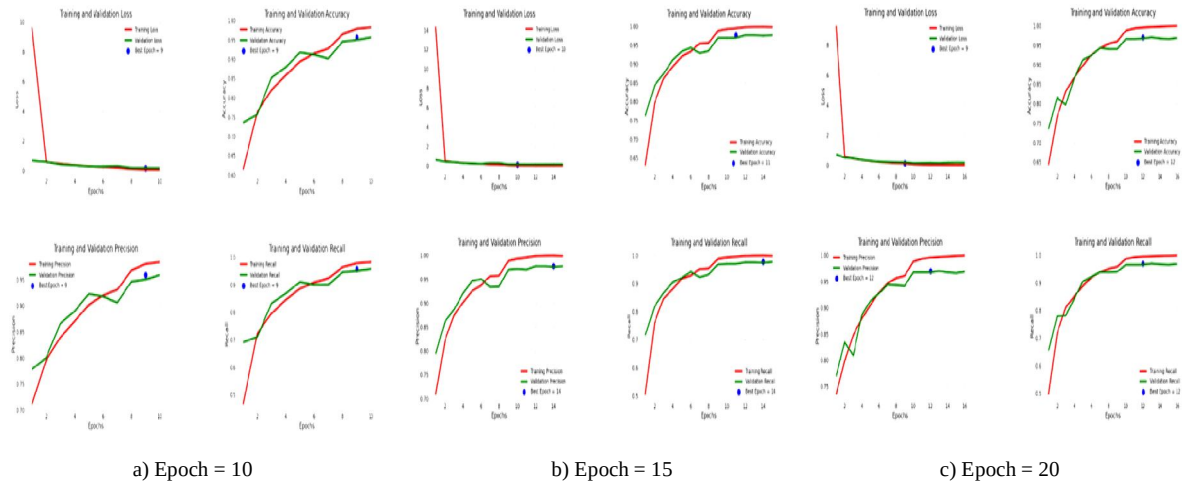


Figure 6. Training progress for the AlexNet model: loss value, accuracy value, precision value, and recall value during training and validation process, Epoch = 10

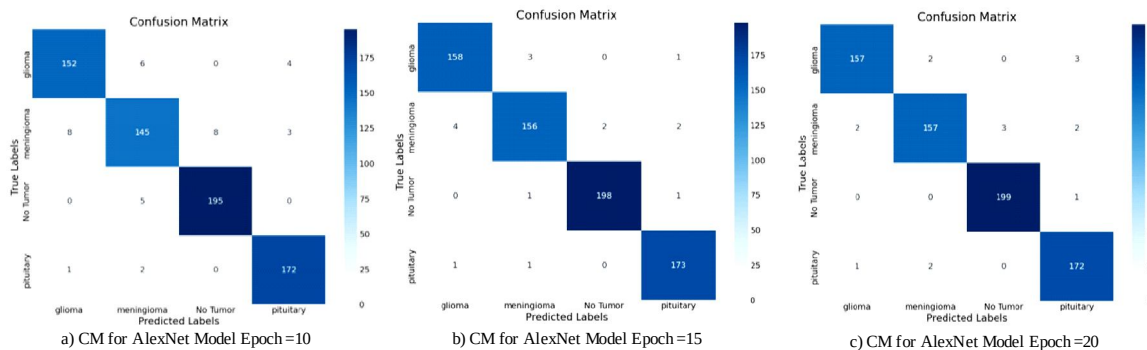


Figure 7. Confusion matrix for AlexNet model for four classes of brain tumor glioma, meningioma, pituitary, and no tumor at different epochs

The model shows strong performance across all metrics (loss, accuracy, precision, recall), with improvements continuing until epoch 9, after which performance stabilizes. The best epoch for the model across all metrics appears to be epoch 9.

The confusion matrix visually represents the model's predicted labels compared to the true labels. Figure 7 illustrates the confusion matrix for these four classes across different epochs (10, 15, and 20).

Figure 8 presents the Receiver Operating Characteristic (ROC) curves, illustrating the model's classification performance across four categories: glioma, meningioma, no tumor, and pituitary, evaluated at different epochs (10, 15, and 20).

Figure 9 demonstrates a sample of the prediction outcomes from the hyper-tuned AlexNet model. Four input images, one from each category, show an almost 100% probability of the predictions.

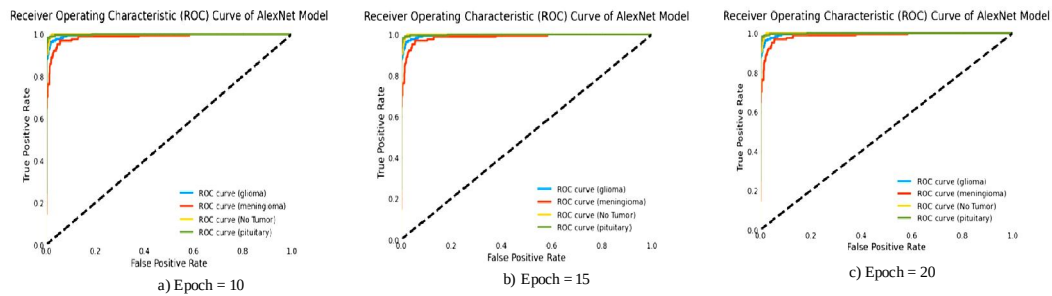


Figure 8. ROC curve for AlexNet model Performance at Epoch = 10, Batch Size = 32

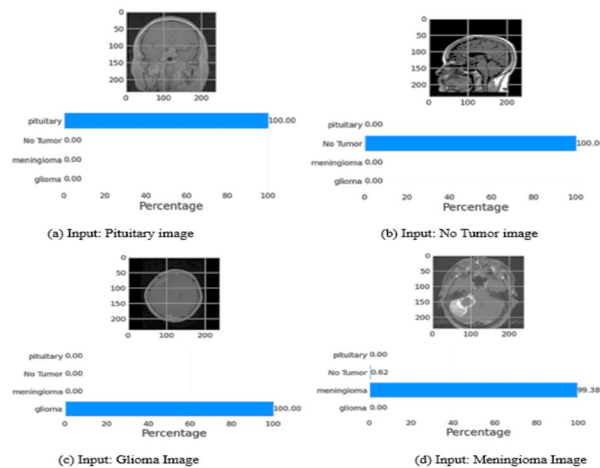


Figure 9. Prediction results of the AlexNet model at epochs = 20, without augmentation, shown almost 100% probability

V. CONCLUSIONS

Brain tumors remain a major medical challenge, making early and accurate detection crucial for improving patient survival and quality of life. This study explores how Convolutional Neural Networks (CNNs), specifically the AlexNet model, can aid in detecting brain tumors from MRI scans. Using 7023 images across four categories—glioma, meningioma, no tumor, and pituitary—the model was fine-tuned with different epochs and the Adamax optimizer. The results were auspicious, achieving 99.31% training accuracy, 96.15% validation accuracy, and 98% test accuracy. Additionally, the model scored a perfect 1.0 in ROC values across all tumor types, showcasing its reliability. These findings highlight AlexNet's strong potential in automating and improving brain tumor diagnosis. Future studies can focus on refining the model further and applying it to even larger datasets, moving closer to scalable, AI-powered diagnostic tools in healthcare.

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