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Optimizing Multi-Class Brain Tumor Diagnosis Using Transfer Learning with EfficientNetB4

Abdelmegeid Amin[a], Mohamed Tony*[a,b], Hassan Shaban[a]

[a]Faculty of Computers and Information, Minia University, Minia, Egypt

[b]Faculty of Computers and Artificial Intelligence, University of Sadat City, Sadat City, Egypt

*Corresponding Author: Mohamed Tony [***mohamed.tony@fcai.usc.edu.eg***]

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ABSTRACT

Certain types of tumors in individuals with brain cancer proliferate rapidly, with their average size doubling within 25 days. Accurately identifying the type of tumor enables physicians to develop effective treatment plans and determine the appropriate dosage. Magnetic Resonance Imaging (MRI) is a critical diagnostic technique for evaluating and diagnosing brain tumors because it provides high-contrast images of brain tissues. This article introduces an innovative approach for multi-classification brain tumors by utilizing deep convolutional neural networks (DCNNs), specifically employing EfficientNet-B4 as the base model, enhanced with fine-tuned, customized layers. Our approach incorporates a Global Average Pooling (GAP) layer to mitigate overfitting, batch normalization, and dropout layers to reduce losses and improve generalization. A series of experiments are performed on an open-access Kaggle dataset to identify the optimal model, utilizing seven optimization algorithms, including Adadelta, RMSprop, Adam, and Nadam. Among all models tested, EfficientNet-B4 with AdamW was the best-performing, achieving a test accuracy of 99.24%, a precision, recall, and F1-score of 99.22% and a specificity of 99.75%. In contrast, EfficientNet-B4 with AdamX had the lowest performance, with a test accuracy of 98.55%, precision of 98.53%, recall of 98.46%, F1-score of 98.49%, and specificity of 98.52%. These innovations can potentially enhance clinical decision-making and improve patient treatment in neuro-oncology.

1. Introduction

The brain, with approximately 100 billion neurons, orchestrates the entire nervous system through its intricate network [1]. The brain is the master control unit, governing the entire nervous system. As a result, any brain anomaly may pose a serious threat to human well-being. The most severe abnormalities are brain tumors. Brain tumors rank among today's most profound and fatal medical conditions. A significant number of deaths occur daily as a consequence of late tumor detection. These deaths could potentially be averted through earlier diagnostic intervention [2]. Brain tumors fall into two categories with vastly different characteristics: benign and malignant. Non-cancerous brain tumors are classified as benign, slow-growing, and stay localized. They are not considered aggressive and do not metastasize [3]. MRI is a powerful imaging technique capable of revealing even the most minor details within the body. It is a standard tool for managing brain lesions and other types of tumors. With MRI, we can predict anatomical structures and locate any abnormalities. This imaging technique offers improved sensitivity compared to CT for detecting changes in tissues and structures and provides information on tumor size [4].

Detecting brain tumors in their early stages is critical, as it provides doctors with the best opportunity to implement effective treatments and improve patient outcomes while reducing costs and saving time for radiologists [5]. Gliomas, meningiomas, and pituitary tumors are examples of intrinsic brain tumors that can cause significant damage and are often challenging to detect early enough for effective treatment. Additionally, if ignored, these tumors can worsen and lead to dangerous situations [6].

Recently, various artificial intelligence (AI) techniques have been employed to automate this process. Within the domain of machine learning (ML), deep learning (DL) uses convolutional neural networks (CNNs) for the task of image classification [7]. CNN is a popularly used method in deep learning that excels at analyzing both 2D and 3D medical images [8]. CNNs are frequently used in medical image analysis due to their high accuracy. However, compared to traditional methods, CNNs have drawbacks: they require large training datasets, are computationally intensive, perform less effectively with limited data, and necessitate significant GPU resources, all of which lead to higher user costs [9]. The selection of appropriate deep learning tools poses a significant challenge as it requires expertise in various parameters, training approaches, and network architectures [10].

Transfer learning (TL) is a widely used method to reduce time and resource requirements when data and computing power are limited. This technique uses pre-trained models by retraining only the final dense layer [11], effectively transferring knowledge from one task to another. TL has proven effective in tumor analysis, particularly for detecting subtle patterns in MRI images. By leveraging models trained on large datasets, the feature extraction process becomes more efficient, improving pattern recognition even with limited data.

Existing CNN-based approaches for brain tumor classification face several challenges. For instance, models like VGG, ResNet, and Inception, while powerful, often require substantial computational resources and are prone to overfitting, especially when trained on limited medical imaging datasets. Additionally, these architectures may not optimally balance accuracy and efficiency, which is crucial for real-world clinical applications. Another limitation is the difficulty in interpreting the decisions made by these models, which can hinder their adoption in medical settings where explainability is paramount.

To address these challenges, this study utilizes EfficientNetB4, a cutting-edge CNN architecture renowned for its scalability and efficiency. EfficientNetB4 employs a compound scaling approach, which proportionally increases the network's depth, width, and resolution to enhance performance while minimizing parameter usage. This makes it an ideal choice for medical imaging applications, where datasets are typically limited and computational resources are constrained. Additionally, its capability to deliver high accuracy with reduced complexity effectively bridges the research gap in designing lightweight yet robust models for brain tumor classification.

This study presents a novel automated brain tumor classification approach using the EfficientNetB4 model, fine-tuned with the proposed custom module. This non-invasive method offers a significant improvement in classification accuracy over traditional techniques. This study's primary research contributions are presented below:

- Proposes a new optimization approach for classifying brain tumors, leveraging a pre-trained EfficientNetB4 model to automatically identify various tumor types.
- Designs a fine-tuning strategy to improve performance when working with small datasets.
- Demonstrates high classification accuracy despite not using data augmentation, showcasing its robustness and generalization.
- Efficiently classifies brain tumors, drastically lowering the time and expertise needed for diagnosis in comparison to traditional methods.
- The fine-tuned EfficientNetB4 model proposed achieves an impressive accuracy of 99.24%, exceeding the performance of other methods reviewed in previous studies.

The paper is organized as follows: A review of the relevant literature in this field is presented in Section 2. Section 3 presents a detailed explanation of the proposed methodology. The software and system requirements, dataset, evaluation metrics, and hyperparameter settings are discussed in Section 4. The results are examined and discussed in Section 5. Section 6 wraps up with an overview of the main conclusions and a discussion of future research directions.

2. Related Work

Over time, various techniques have been developed to detect brain tumors through MRI scanning, ranging from classic methods of image processing to machine learning approaches based on neural networks. In [12], the authors introduced a block-based fine-tuning method for classifying brain tumors, leveraging a pre-trained VGG19 model via transfer learning. This adaptable approach, tested on the

Figshare brain tumor dataset, does not rely on a feature extractor. A mean test accuracy of 94.82% was achieved through cross-validation using 5-fold with minimal preprocessing requirements. In the study [13], a deep neural network (DNN) with “an auto-encoding module” was employed for classifying brain tumors. Prior to DNN processing, the images were segmented, and both “intensity-based and texture-based features” were extracted using a “Gray-level co-occurrence matrix (GLCM) and discrete wavelet transform (DWT).” These features were then input to a DNN consisting of two autoencoders and a softmax classifier.

In [14], five widely used deep learning architectures were utilized to develop a brain tumor diagnosis system. They applied the DenseNet201, Xception, ResNet152V2, DenseNet121, and InceptionResNetV2 models for multi-classification tasks. The results indicated that the Xception-based model achieved 95.8% accuracy, outperforming other models in four-category classification.

The authors in [15] achieved 98% accuracy in classifying three types of brain tumors by using a pre-trained GoogLeNet for feature extraction from brain MR images, followed by a deep CNN for classification. In [16], the authors introduced a CNN model for classifying brain MR images into categories of normal, normal tissue, abnormal tissue, and both low-grade and high-grade gliomas. They achieved 91% accuracy by adapting the AlexNet CNN model for their architecture.

The authors in [17] tested several CNN models, including Inception-V3, DenseNet201, GoogleNet, ResNet50, and AlexNet, for brain MRI image classification, achieving reasonable accuracies. The highest accuracy of 97.2% was achieved through the modification of a pre-trained ResNet-50, involving the removal of its last five layers and the addition of eight new ones. In addition, the authors in [18] employed transfer learning with “VGG-16, Inception-V3, and ResNet-50” models for the classification of brain tumor data, with ResNet-50 demonstrating the highest accuracy at 95%. In [19], the authors achieved 97.3% accuracy with their multi-pathway CNN framework for the automated segmentation of glioma, meningioma, and pituitary tumors using a public “T1-weighted contrast-enhanced MRI dataset.”.

In [20], two separate CNN models were developed, with 13 and 25 layers, respectively, for classifying brain images. The study found that the accuracy decreased to 92.66% when classifying into five classes compared to two. Additionally, using two distinct models for detecting and identifying brain tumors was highlighted as a drawback. The authors in [21] proposed a two-phase approach to classify tumors involving the creation of an offline database and its subsequent use in an online learning phase. The offline stage sequentially processed brain tumor images through segmentation, tumor extraction, and metric-based learning for distance measurement. During the online learning phase, the extracted features of newly acquired images were compared with pre-calculated distance metrics stored in an offline database, achieving a classification accuracy of 94.68%.

In summary, the reviewed studies demonstrate that deep learning significantly improves accuracy in brain MRI classification compared to conventional methods. However, these models based on deep learning require extensive training data to outperform conventional ML methods. Therefore, in this work, EfficientNetB4 is used to enhance the performance of brain MRI classification, utilizing its efficient architecture to achieve higher accuracy while minimizing computational resource requirements.

3. Proposed Methodology

This section presents the classification methodology utilized to analyze and categorize brain tumor types based on MR imaging data. The procedural flow for the classification of brain tumors is depicted in Figure 1. The process is divided into four stages. Stage 1 involves cropping, resizing, splitting, and normalizing the dataset. Stage 2 uses the pre-processed images as input to the EfficientNetB4 architecture, which serves as the feature extractor for the proposed approach. Stage 3 processes the features extracted by this pre-trained model through additional layers, such as dropout and batch normalization, to reduce the risk of overfitting. Finally, Stage 4 employs a softmax classifier to categorize the processed features obtained from the pre-trained model and the custom layers. Finally, the trained models are assessed using standard classification metrics, including Precision, Accuracy, F1-score, Specificity, and Recall.

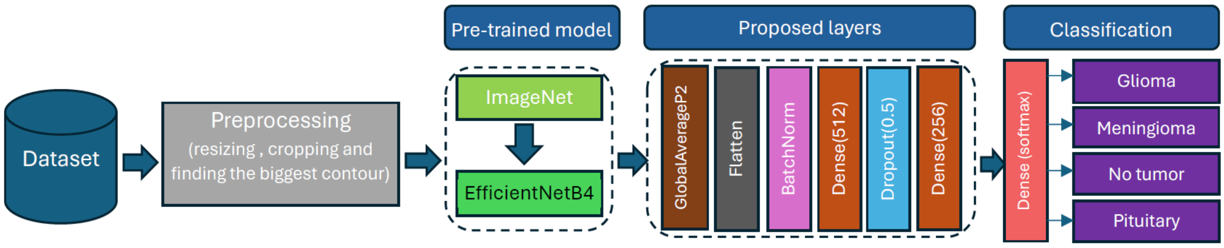

FIGURE 1. Outline of the Proposed Model Workflow

3.1. Preprocessing Stage

In the data preprocessing stage, the dataset is prepared to improve the machine learning model's performance. The pre-trained model requires images with dimensions of 240 × 240 × 3, so input images are resized accordingly. The preprocessing process involves cropping MR images by identifying the brain contour and removing extraneous parts. This is done by converting the image to grayscale, applying a Gaussian blur, and utilizing Otsu's thresholding technique to distinguish the brain region from the background. The largest contour, representing the brain, is selected, and its outermost points are marked and used to crop the image. After cropping, the dataset was split into an 80:20 training-to-testing distribution. No data augmentation techniques were employed, as the main objective was to achieve high accuracy through transfer learning without depending on augmentation or large datasets. We leveraged pre-trained models that had already been trained on extensive datasets, allowing them to capture rich feature representations. Due to the knowledge these models already possess, data augmentation was deemed unnecessary for transfer learning in this scenario. Although the "No Tumor" class has a slightly larger number of samples than the others, the dataset does not show a significant class imbalance. To ensure balanced learning and minimize bias, weighted loss functions were applied, with class weights calculated based on the inverse frequency of each class in the training data.

3.2. Feature Extraction Stage

Feature extraction involves the conversion of the information in a dataset into a more interpretable and meaningful format. It leverages the architecture of an ImageNet-pre-trained model with its top layer removed. This architecture is then supplemented with an additional classifier for further processing. Features extracted using this architecture are subsequently passed into the classifier. In this study, the deep learning model EfficientNetB4 was fine-tuned by adjusting its final layers, and the pre-trained model's architecture was utilized for feature extraction.

3.2.1. Transfer learning

Transfer learning (TL) includes leveraging a pre-trained model, generally trained on a substantial dataset, and adapting it through fine-tuning for application to a different dataset. Figure 2 shows how transfer learning works. In deep learning, the two primary approaches to TL are fine-tuning and feature extraction. Models pre-trained on extensive datasets like ImageNet provide valuable pre-trained weights for transfer learning. These models can be used directly as feature extractors, enabling effective analysis of smaller datasets, such as brain MRI images. Alternatively, fine-tuning allows us to adapt these models to specific tasks. Rather than just extracting features, this approach involves using the pre-trained model’s weights and modifying them throughout the learning process. This allows the model to be tailored to the task at hand without completely losing the knowledge gained during the original training. Transfer learning provides several key benefits: faster training, reduced overfitting, the ability to train with smaller datasets, and improved performance. In this study, the EfficientNetB4 model was selected as the pre-trained CNN architecture for transfer learning owing to its exceptional balance between accuracy and computational efficiency. Its pre-training on the ImageNet dataset provides robust feature extraction capabilities, which is particularly advantageous for applications in medical imaging, such as classifying brain tumors, where the ability to capture fine-grained details in MRI images is essential for accurate diagnosis. Furthermore, the model's scalable design facilitates reliable classification outcomes while maintaining efficiency, rendering it an ideal choice for this research.

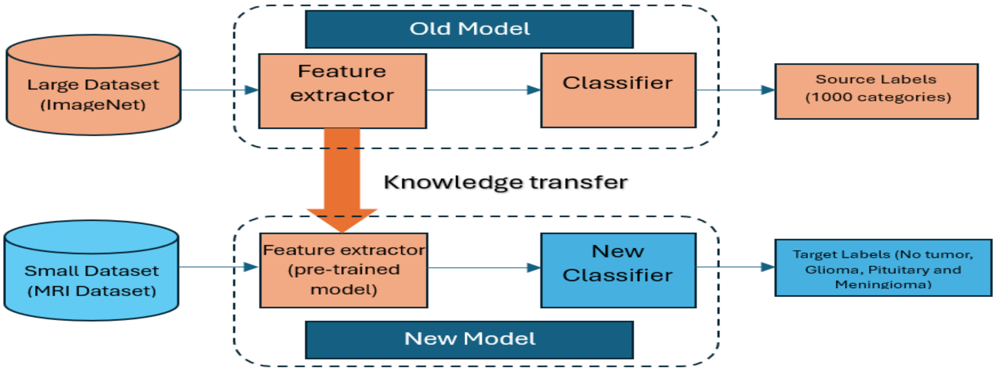

FIGURE 2. The concept of transfer learning

3.2.2. EfficientNetB4

EfficientNetB4, a member of the EfficientNet family, is designed to be both small and computationally inexpensive yet still deliver high performance in tasks like image classification within computer vision. EfficientNetB4 is bigger and stronger than previous versions like B0, B1, B2, and B3. EfficientNetB4 [22, 23] is both deeper and wider compared to its earlier versions. It is distinguished by its “compound scaling” approach, which enhances the network's depth, width, and resolution simultaneously. This approach enhances performance while keeping computational costs relatively low. EfficientNetB4 is composed of 7 blocks that progressively reduce the image size from an initial 256 x 256 resolution to 7 x 7. EfficientNet achieves high performance with a reduced number of parameters through its scalable CNN architecture. First introduced in the paper [24], The model achieves competitive results while minimizing computational costs through the optimization of width, depth, and resolution. In our study, we utilized EfficientNetB4, a specific version of this model [25, 26]. The choice to use EfficientNetB4 from the range of EfficientNet models (ranging from B0 to B7, including B2V2) was made following thorough evaluation and experimentation. EfficientNetB4, along with other variants in the EfficientNet family, is used to emphasize the improvements in both accuracy and computational efficiency. Fig. 3 illustrates the modified EfficientNetB4 architecture, which has been adapted for multi-class classification.

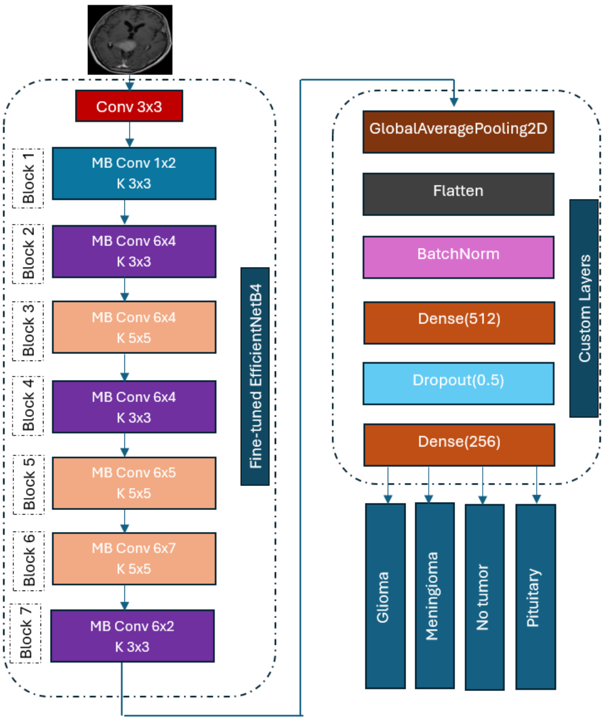

FIGURE 3. Fine-tuned EfficientNetB4 Architecture

3.3. Feature Optimization During Training

At this stage, the features obtained from the pre-trained EfficientNetB4 model are further optimized through the application of several layers. First, a GlobalAveragePooling2D layer reduces the spatial dimensions of the extracted features. This is followed by a Flatten layer, which transforms the pooled features into a 1D vector. To stabilize the learning process, a Batch Normalization layer is applied, ensuring consistent performance during training. A fully connected Dense (512) layer is then introduced, followed by a Dropout (0.5) layer to randomly deactivate 50% of the neurons to prevent overfitting. Finally, another Dense (256) layer refines the features before they are passed to the next stage. These enhancements make the model more robust and better suited for classification in the final step.

3.4. Classification Methodology

In the classification stage, a dense layer with a softmax activation function is employed to categorize the features processed by the pre-trained model and additional layers. The proposed EfficientNetB4 model was trained on the “Figshare Brain Tumor MRI Dataset.” To improve classification performance, the model automatically adjusts the weights of its various layers. The pre-trained EfficientNetB4 model then extracts features from both the training and testing images. Extracted features are fed into additional layers to enhance the model's performance. Finally, the softmax classifier utilizes the extracted features to categorize the tumors into four distinct types.

4. Experimental setup

Our experiments are conducted using Google Colab, a public notebook platform. The model is trained on an “NVIDIA L4 Tensor Core GPU with 24GB of GDDR6 RAM.” The system incorporates 53 GB of high-capacity RAM. It utilizes the 22.5 GB of GDDR6 memory provided by the NVIDIA L4 GPU to facilitate the efficient processing of large datasets and complex models, resulting in enhanced AI performance [27]. The code is written in Python, using TensorFlow (backend) and Keras (frontend) for model development.

4.1. Dataset

The training, validation, and evaluation of the proposed approach were conducted using an openly accessible MRI dataset of brain tumors obtained from Kaggle [28]. Table 1 shows the dataset includes 7,023 brain MRI images. The dataset is partitioned into four distinct classes. The distribution of images within each class is as follows: Gliomas (1,321 training, 300 testing), Meningioma (1,339 training, 306 testing), No Tumor (1,595 training, 405 testing), and Pituitary (1,457 training, 300 testing). The dataset was split into 80% for training and 20% for testing. No data augmentation techniques were applied, as the primary goal was to achieve high accuracy through transfer learning without relying on augmentation or large datasets. We utilized pre-trained models, which had already been trained on extensive datasets, enabling them to capture rich feature representations. Given the prior knowledge these models possess, we found it unnecessary to apply data augmentation specifically for transfer learning in this context. Although the "No Tumor" class has a slightly higher number of samples compared to the others, the dataset does not exhibit severe class imbalance. To ensure balanced learning and mitigate potential bias, weighted loss functions were employed, with class weights calculated based on the inverse frequency of each class in the training data.

TABLE 1: Overview of the dataset

Class	Training Images	Testing Images
Gliomas	1,321	300
Meningioma	1,339	306
No Tumor	1,595	405
Pituitary	1,457	300

4.2. Performance Metrics

A Confusion Matrix (CM) is used to visualize, compile, and assess the results of DL and ML models. A CM is a table that demonstrates the classifier's performance. The CM is composed of four key properties that define the classifier's performance metrics. These four parameters are:

True Positive (TP): The count of cases where the model correctly predicted 'yes' (in this study, this refers to individuals who actually have the disease, and the model accurately identified them).

True Negative (TN): The total number of cases where the model correctly predicted 'no' (in our study, this means the individuals do not have the disease, and the model accurately identified them).

False Positive (FP): The total number of cases where the model incorrectly predicted 'yes' (in our study, this means the individuals do not actually have the disease, but the model incorrectly predicted that they do).

False Negative (FN): The total number of cases where the model incorrectly predicted 'no' (in our study, this means the individuals actually have the disease, but the model incorrectly predicted they do not).

Performance metrics include classification accuracy, precision, recall, specificity, and F1-score. These are calculated as shown in equations (1), (2), (3), (4), and (5) below to compare and evaluate our proposed methods.

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FP+FN+TN)} \qquad (1)$$

$$\text{Precision} = \frac{TP}{(TP+FP)} \qquad (2)$$

$$\text{Recall} = \frac{TP}{(TP+FN)} \qquad (3)$$

$$\text{Specificity} = \frac{TN}{(TN+FP)} \quad (4)$$

$$\text{F1-score} = 2 \text{ x } \frac{precision\ x\ recall}{precsion+recall} \quad (5)$$

4.3. Hyperparameter Configurations

Hyperparameter optimization is the process of determining the optimal parameter values for a machine learning model to enhance its performance, accuracy, and generalization on a given dataset. In this study, hyperparameter tuning was conducted to optimize the Dropout Rate, Batch Size, Optimizer, and Learning Rate for fine-tuning the pre-trained EfficientNetB4 model. To systematically search for the best hyperparameter values, a Genetic Algorithm (GA) was employed, an evolutionary optimization technique that iteratively selects and refines the best hyperparameter combinations based on fitness evaluation. The search space included learning rates (0.0001, 0.001, and 0.01), batch sizes (16, 32, and 64), optimizer settings (AdamaX, Nadam, and AdamW), and dropout rates (0.2, 0.3, and 0.5). The GA was run for 10 generations with a population size of 10, selecting the best-performing configuration based on validation accuracy. The optimal hyperparameter setup consisted of the AdamW optimizer, a learning rate of 0.0001, a batch size of 32, and a weight decay of 0.01. By leveraging GA, this study efficiently explored a large hyperparameter search space, avoiding manual trial-and-error tuning while achieving an optimal balance between performance and generalization. Additionally, regularization techniques, such as dropout (rate = 0.2), were applied to prevent overfitting, ensuring robust model performance.

TABLE 2: The chosen hyperparameters and their values for the experiments

Parameter	**values**
No. of epochs	20
Batch Size	[16, 32, 64]
Validation split	0.2
Activation (Output Layer)	softmax
Loss Function	‘Categorical cross-entropy’
Optimizers	[NADAM, AdamX, and AdamW]
Learning Rates	[0.0001, 0.001, 0.01]
Dropout Rates	[0.2, 0.3, 0.5]

5. Results and Discussion

This article presents a method for classifying four types of brain tumors from MRI data using a pre-trained EfficientNetB4 neural network optimized through hyperparameter tuning. To determine optimal features, we tested the learning networks with three optimizers (AdamX, Nadam, and AdamW) and learning rates of (0.01, 0.001, and 0.0001). The existing network was augmented with several-layer dense neural networks after feature extraction. After all the experiments, we identified the model's top performance based on the highest values for each metric. An in-depth analysis of the EfficientNetB4 model's classification performance, using various metrics, is presented in Table 3. As shown in Table 3, the AdamW optimizer performs the best, achieving 99.24% accuracy, 99.22% precision, 99.22% recall, an F1-score of 99.22%, and a specificity of 99.75%. The AdamX optimizer yields the lowest classification performance, with a test accuracy of 98.55%, precision of 98.53%, recall of 98.46%, specificity of 99.52%, and an F1-score of 98.49%.

Table 3: The EfficientNetB4 model's performance was assessed using a range of optimizers and evaluation metrics

Optimizers	**Accuracy**	**Precision**	**Recall**	**specificity**	**F1-score**
Nadam	98.93	98.89	98.89	99.65	98.89
AdamW	**99.24**	**99.22**	**99.22**	**99.75**	**99.22**
AdamX	98.55	98.53	98.46	99.52	98.49

The proposed approach, utilizing the EfficientNetB4 model optimized with the AdamW optimizer and fine-tuned using the best hyperparameter configurations, demonstrated exceptional efficiency in brain tumor classification across four distinct categories: Glioma, Meningioma, Pituitary tumors, and No tumor. Table 4 highlights the category-specific evaluation metrics, where the model achieved outstanding Precision, Recall, Specificity, F1-score, and Accuracy across all tumor types. For Glioma, the Precision was 99.01%, Recall 99.67%, Specificity 99.70%, F1-score 99.34%, and Accuracy 99.69%. Similarly, Meningioma achieved a Precision of 98.68%, Recall 98.04%, Specificity 99.60%, F1-score 98.36%, and Accuracy 99.24%. The Pituitary tumor category demonstrated remarkable performance with a Precision of 99.67%, Recall of 99.67%, Specificity of 99.90%, F1-score of 99.67%, and Accuracy of 99.85%. Lastly, the No Tumor category achieved a Precision of 99.51%, Recall of 99.51%, Specificity of 99.78%, F1-score 99.51%, and Accuracy of 99.69%. These results underscore the effectiveness of the AdamW optimizer, combined with optimal hyperparameter tuning, in enhancing the performance of the EfficientNetB4 model for accurately identifying and classifying brain tumor types with high reliability.

Table 4: Evaluation Metrics per Category for the Proposed Model

Model	**Tumor category**	**Precision**	**Recall**	**specificity**	**F1-score**	**Accuracy**
Fine-Tune EfficientNetB4	Glioma	99.01	99.67	99.70	99.34	99.69
	Meningioma	98.68	98.04	99.60	98.36	99.24
	Pituitary	99.67	99.67	99.90	99.67	99.85
	No Tumor	99.51	99.51	99.78	99.51	99.69

5.1. Discussion

This subsection emphasizes the EfficientNetB4 model's efficacy in classifying brain tumors. The use of the AdamW optimizer and fine-tuned hyperparameters significantly contributed to the model's strong generalizability and performance. The evaluation of the proposed approach is supported by accuracy and loss curves, along with the confusion matrix, which highlights the model's robustness in achieving precise and reliable outcomes.

The training procedure for the FineTuned-EfficientNetB4 model, optimized with the AdamW optimizer and fine-tuned using the best hyperparameters, is depicted in the accuracy and loss curves presented in Fig. 4. The loss graph shows a consistent and smooth decline in both the training and validation loss over 20 epochs, indicating effective convergence of the model without signs of overfitting. Similarly, the accuracy graph demonstrates a rapid improvement in both training and validation accuracy during the initial epochs, eventually stabilizing near-optimal values. The validation accuracy closely follows the training accuracy, further emphasizing the generalizability of the model. These graphs confirm the stability and efficiency of the training process in achieving high performance across the evaluated metrics.

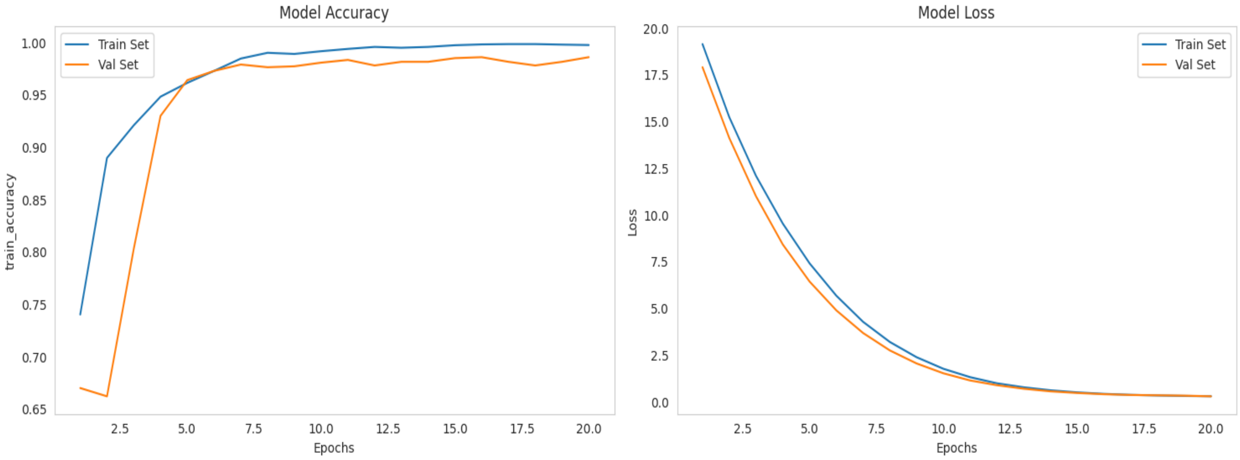

FIGURE 4. Accuracy and loss curves of the fine-tuned EfficientNetB4

Figure 5 illustrates the CM for a classification model trained to diagnose four medical conditions: glioma, meningioma, pituitary tumors, and no tumor ("notumor"). In this matrix, the vertical rows indicate the true condition, while the horizontal columns show what the model predicted. The model exhibits excellent performance with minimal misclassifications. For glioma cases, 299 out of 300 were accurately identified, with only one error. Similarly, for meningioma, 300 cases were correctly classified, though three were misclassified as glioma, and two were misclassified as "notumor." Pituitary tumors were identified with only one error, while "notumor" cases were nearly perfect, with only two misclassified as meningioma. With an overall accuracy of 99.24% and a low misclassification rate of 0.76%, the model provides a reliable diagnostic tool. This high performance indicates its potential to support healthcare professionals in accurately identifying these conditions.

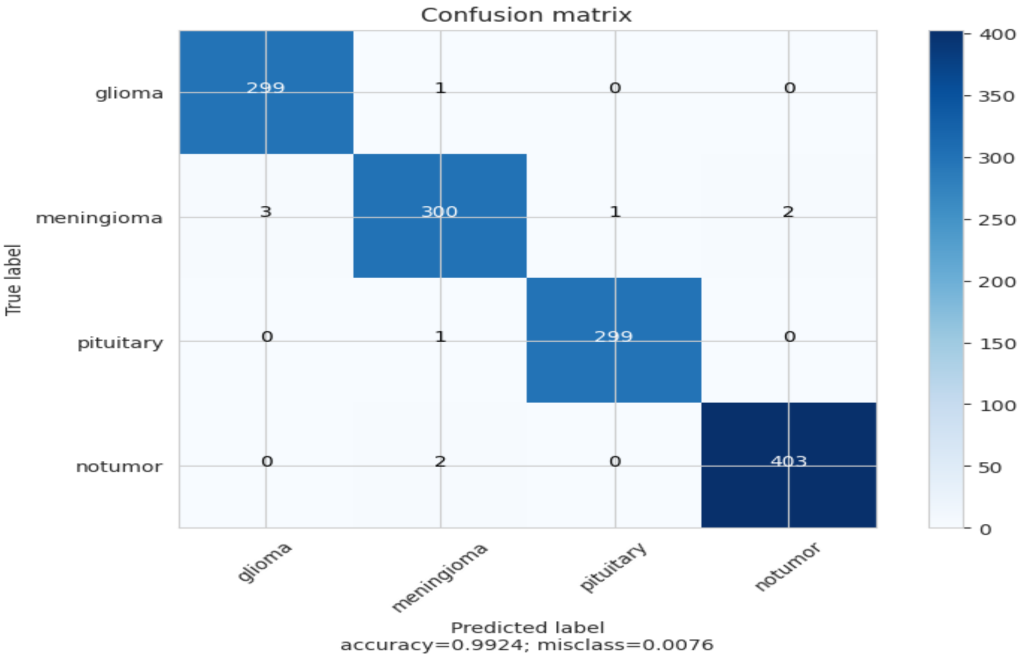

FIGURE 5. Fine-tuned model confusion matrix

Furthermore, Table 5 presents a detailed performance comparison between the current study and recent research efforts that employed ML and DL techniques for brain tumor detection. It also highlights the outstanding performance of the proposed model, achieving an overall accuracy of 99.24% and surpassing other advanced methods in brain tumor detection.

Table 5: An assessment of the proposed model's performance in comparison to recent advanced methods

Optimizers	**Method**	**Accuracy**
Sajjad et al. [29]	Vgg 19	87.4%
Shah et al. [30]	Fine-tuned EfficientNetB0	98.8%
Noreen et al. [31]	Inception-v3-Ensemble	94.34%
Zulfiqar et al. [32]	Fine-tuned EfficientNetB3	98.21%
Proposed Model	**Fine-tuned EfficientNetB4**	**99.24%**

6 Conclusion and Future Work

This study demonstrates the effectiveness of transfer learning with pre-trained models for classifying MRI images into four categories: normal tissue and three types of brain tumors—gliomas, meningiomas, and pituitary tumors. Using the EfficientNetB4 model, the performance of three optimization algorithms—Adamax, Nadam, and AdamW—was compared. The proposed model achieved remarkable results, including 99.22% precision, 99.22% recall, 99.75% specificity, 99.24% accuracy, and an F1-score of 99.22%. A set of experiments was carried out to evaluate the impact of different learning rates on a combined dataset comprising "Figshare, SARTAJ, and BrH35." The success of the proposed system is attributed to two critical factors: the use of a robust deep-learning architecture and access to a diverse, well-curated dataset. By leveraging the EfficientNetB4 model, which excels in extracting meaningful features from images, our fine-tuned approach outperforms several cutting-edge methods for similar classification tasks, achieving an impressive overall test accuracy of 99.24% with the AdamW optimizer. Specifically, **EfficientNetB4 with AdamW demonstrates superior performance compared to other optimization algorithms like Adamax and Nadam, which further emphasizes the effectiveness of this approach.** Our findings underscore the potential of deep learning to expedite brain tumor diagnosis via MRI analysis, thereby offering promising avenues for improved patient care and optimized treatment strategies.

In the future, a transformer-based approach could be explored as an alternative to deep CNN-based methods for brain tumor classification, enabling the generation of rich feature maps while reducing network complexity. Additionally, integrating multi-modal data—such as combining MRI scans with clinical records or genetic information—could enhance diagnostic accuracy and model robustness. Exploring the impact of larger and more diverse datasets would also be beneficial in improving generalizability and reducing potential biases. These directions offer promising avenues for further advancing automated brain tumor classification."

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