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Enhanced Brain Tumor Diagnosis with EfficientNetB6: Leveraging Transfer Learning and Edge Detection Techniques

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Correct identification of brain tumors is crucial for determining the subsequent steps in patient management and prognosis. This study introduces a novel approach by mimicking three enhanced deep learning models EfficientNetB0, EfficientNetB6, and ResNet50 on a dataset of 7022 MRI instances, each depicting one of four varieties of brain tumors. The research was conducted using advanced neural network architectures, leveraging transfer learning to improve model performance. Results indicated that EfficientNetB6 achieved the highest testing accuracy at 99.39%, outperforming EfficientNetB0 and ResNet50, which recorded test accuracies of 95% and 97% respectively. Evaluation metrics further highlighted the superior performance of EfficientNetB6, with a precision, recall, and F1 score all at 99%. These findings demonstrate the significant potential of deep learning algorithms in enhancing the diagnostic accuracy of brain tumors, suggesting their implementation in clinical settings could lead to better diagnosis and treatment options.

Keyword: Brain tumor; Medical imaging; Computer-aided diagnosis; EfficientNetB6; Transfer learning

Introduction

All types of brain tumors are most dangerous and deadly in both the pediatric and adult populations, accounting for 85-90% of all primary Central Nervous System (CNS) tumors. Each year, an estimated 11,700 new cases are diagnosed [1]. Malignant brain and CNS tumors have particularly poor prognoses, with a 5-year survival rate of 34% for men and 36% for women. Hence, efficient therapy is vital to enhance the chances of successful treatment and proper identification of health conditions [2]. Brain tumors can be classified in many ways but the most significant classifications are based on behavior, namely whether they are benign cancers or malignant cancers; or according to their location, specifically pituitary tumors. Enhanced diagnostic accuracy can significantly impact disease management, leading to increased survival rates and improved quality of life for those affected [3][10][11].

MRI is the most accurate method for identifying brain tumors generating abundant image data that the radiologist must review. However, manual analysis of these images can be inaccurate due to the complexity of brain tumors and the significant variability in their characteristics [2][4]. Consequently, automated classification methods using Machine Learning (ML) and Artificial Intelligence (AI) have been developed, offering better accuracy compared to manual approaches. These methods are particularly better than the normal techniques with a large data set, minimizing the errors that might be caused by manual calculations and also providing more generalized and standardized results adding incorrect diagnosis and treatment of patients with brain tumors [4][12][13].

This paper aims to design a DL-based system for the identification and categorization of HGBs, where three types of DL techniques, namely CNN, ANN, and TL are integrated [5]. These techniques are quite reliable especially since they are designed to analyze large data sets and recognize the subtler patterns; these techniques could greatly help radiologists and other health professionals. These DL algorithms entail the analysis of MRI images with all the problems associated with the diagnosis stage being effectively managed and leading to greater efficiency in the treatment of patients and improved health outcomes among patients [6][7][8][9][5][10].

The purpose of this study is to develop an automatic method to detect and determine the type of brain tumor using MRI images as inputs. To achieve this, the study employs deep learning technologies, specifically Convolutional Neural Networks (CNN) and Transfer Learning (TL). Due to the large variability and inherent textural complexities of the mammalian brain tumor images, the strategy of transfer learning is especially beneficial given the limited sample size of the available training set. In the current study, the pre-trained weight of the CNN model was EfficientNetB6, which proved efficient and robust for image classification tasks. Incorporating several architectural features to reduce computational complexity while increasing accuracy, EfficientNetB6 can efficiently identify diseases based on intricate structures of medical images in real time.

Objectives and Novelty:

- An accurate Deep CNN model is to be designed for the correct and early detection of brain tumors using MRI images.
- Ensure that the MRI has a large and varied set of samples typical of all stages of brain tumor for training and fine-tuning the Deep CNN.
- Precise the Deep CNN by applying methods including transfer learning and data augmentation to enhance the accuracy of 'illness classification'.
- Sensitivity, specificity, precision, and accuracy standards to determine the efficacy and benefits of the generated model in early and accurate identification of brain tumors.

- Establish the efficiency of the Deep CNN model by comparing it with the conventional diagnostic methods and analyze the improved feature of early detection and classification process for the brain tumor.

Related Work:

The classification of brain tumors using machine learning and deep learning has been an active area of research. Numerous studies have demonstrated the efficacy of various approaches, particularly those leveraging the power of CNNs and TL. Sun et al. [1] have analyzed a work that proposed CNN for the classification of the MRI brain scans of the patients and as per the findings of this work, it has showcased much higher levels of accuracy than the conventional methods. Sun and his colleague's work involved the use of MRI scans, and augmentation of the images to enhance features relevant to the classification process, the deep CNN was then used to classify the different types of tumors present in the brain. The study also confirmed the utility of CNNs in identifying specific features in MRI data that are not detectable through simple viewing. In the case of their study, Sun et al. have contributed to improved functionalities of CNNs and the functioning of automated classification technology for brain tumors and proved to be valuable to practitioners in the medical field by providing improved diagnostic solutions.

Zhao et al. [2] aimed to enhance our understanding of the use of Transfer Learning in brain tumor classification. The researchers utilized feature extractors derived from large datasets, fine-tuned for specific MRI brain scan data, resulting in high classification accuracy with minimal training time. This approach leverages the learned features from large-scale image classification tasks used and then applies them with modifications to the specific context of the problem at hand, to the specific context of detection of brain tumors. Zhao et al. demonstrated that the features learned in general image classification transfer effectively to medical imaging, improving the accuracy and robustness of brain tumor classifiers. This kind of work has shown potential to revolutionize the qualification paving the way for advancement in diagnosis and treatment in neuroimaging.

Shankar et al. [4] have provided a broader survey discussing the proficiency of different algorithms in the classification of brain tumors. They found that deep learning models, particularly those employing Convolutional Neural Networks (CNNs) and Transfer Learning, achieved superior results compared to traditional machine learning tools like Support Vector Machines (SVMs) and Random Forests. It is essential to choose high-quality data and applying the right preprocessing techniques to improve the accuracy of the model. Regarding the potential of deep learning in the field of brain tumor diagnostics, the survey clarified the importance of the neural network application that would tightly combine the most progressive architectures and through transfer learning would adapt the models that had been trained on other data sets for the medical imaging data. These outcomes raise awareness of the value of increased effectiveness and the development of machine learning techniques, which can improve the diagnosis and development of medical images and support more accurate decision-making in the clinical treatment of patients.

Chen et al. [6] proposed the concept of combining a CNN with ANNs to enhance quality in classification. This approach leverages CNNs' ability to extract features from MRI data and ANNs' strength in decision-making based on these features, resulting in an ensemble classification system well-suited for complex MRI datasets. CNNs were used in combination with ANNs as proposed by Chen et al., which showed that the combination of both structures has provided major steps in the direction of the improved diagnostic analysis of brain tumors and, therefore, it can be inferred that there is a lot of potential for the enhancement of the hybrid CNN-ANN in neuroimaging diagnostics and helping patients.

Dong et al. [7] proposed the concept of classification of brain tumors in their study dated 2020. They demonstrated that ResNet50 could learn hierarchical structural features from

MRI images beyond the initial level, achieving high classification rates. Through the employment of residual learning ideology, ResNet50 significantly improved the process of extracting representative features that are instrumental in the differentiation of various brands of tumors. Compared to other areas involved with deep learning-based approaches, ResNet50 holds a bargain for enhancing medical image analysis and presents realistic future horizons for more accurate diagnoses in neuroimaging.

Shi et al. [8] used VGG-19 in Nigeria for the classification of brain tumors. Their technique was used to fine-tune the VGG-19 network to MRI images which proved relatively effective at the last stage of fine-tuning in classifying between malignant and benign tumors. Kumar and Kaur [9] discussed the integration of ensemble learning techniques with CNN for the classification of brain tumor images. However, Weisz and Bernstein further argued that combining results from multiple models could enhance classification performance as each model brings unique strengths to the table.

These analyzed studies revealed the capability of deep learning and transfer learning in changing the paradigm of brain tumor classification. Building on the insights from these seminal papers, this study aims to develop an advanced classification system to improve diagnostic precision. This system aims at improving the precision of diagnosis because differentiating between a healthy individual and a patient with a particular disease or condition can assist many clinicians in arriving at proper decisions while practicing. This study aims to add to the body of knowledge by using deep learning and transfer learning models as modern tools for enhancing patient outcomes of those with brain tumors and improving their treatment.

Proposed Method:

The proposed study aims to develop a model that can accurately classify the brain tumor with a high degree of confidence in its ability to classify new, unseen images. This model will serve as a smart identification tool for the doctors and will be integrated into a friendly user interface. The proposed study entails a general plan of operation which is highlighted in the flowchart in Figure 1 below.

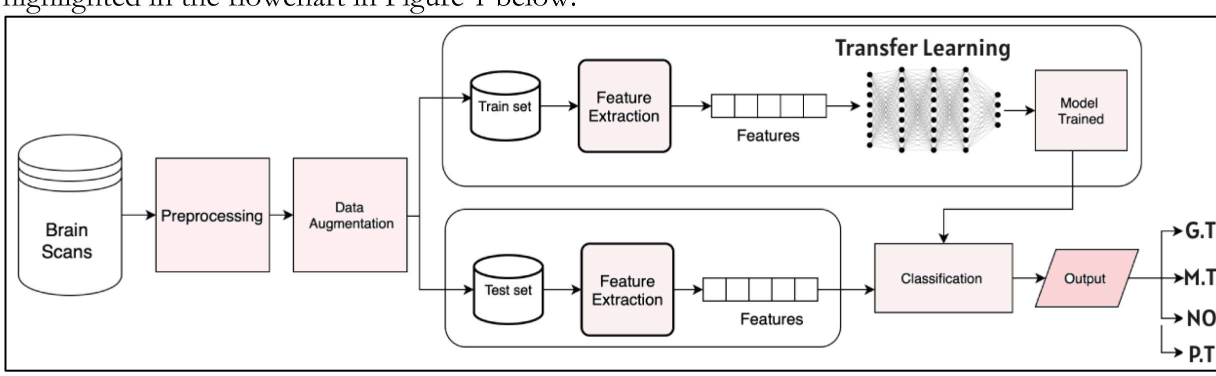

Figure 1: Shows the Flow Diagram of the Work

The flowchart displays the general workflow for classifying brain scans using a transfer learning method. The process begins with preprocessing the brain scans to standardize and adjust the data. Data augmentation is then performed to expand the dataset, providing a broader sample. The augmented data is then split into a training set, features are extracted, these features are used in a transfer learning approach where a broad model with features learned from the target domain is refined and trained more especially to categorize brain scans. After training, the model's performance is assessed using a separate test set, where features are extracted and classified by the trained model. The final output categorizes the brain scans into four categories glioma tumor, meningioma tumor, no tumor, and pituitary tumor can be related to. By employing transfer learning and structured data processing into this model, the added workflow further strengthens the model's precision and ability to generalize.

Data Collection:

The dataset used in this study was sourced from the Kaggle website which is available on Google, comprising images categorized into four classes of brain tumors glioma tumor, meningioma, no tumor, and pituitary tumor. This dataset, combined with accomplished segmentation work, consists of 7,022 images. This partitioning strategy ensures that the model is trained on a diverse set of tumor types while preserving a separate set for evaluating the model's performance on unseen tumor forms. This approach aids in developing an efficient brain tumor classification model that can accurately differentiate between various tumors from MRI images. The resulting classification model has significant potential for diagnosing rarities in clinical practice, thereby enhancing diagnostic precision and supporting clinical decision-making.

Image Preprocessing:

Before training the deep learning model, the dataset underwent preprocessing to optimize its quality for accurate brain tumor classification. Initially sourced from Kaggle website, the dataset comprised 7,022 MRI images categorized into four classes: glioma tumor, meningioma, no tumor, and pituitary tumors [11]. The preprocessing involved resizing all images to a standard dimension of approximately 224 pixels on each side, along with cropping and padding to ensure they fit this dimension. Image-enhancing methods such as random rotations, flipping, shifting, and zooming were used in enhancing the training data so that the model could generalize well in its interactions with other unseen images. To overcome problems with class imbalance special procedures like the incorporation of weights in the classes used during learning to balance the different classes were employed. Furthermore, a portion of the training data was reserved for validation purposes, allowing for periodic assessment of the model's performance and optimal parameter tuning. In this case, the preprocessing methods discussed served as a means of enhancing the integrity of the dataset and also established a robust foundation for developing a powerful brain tumor classifier.

Data Augmentation:

To increase the variety and number of images in our training set for more effective transfer learning for the classification of brain tumors, several instances of data augmentation were used. These included factors such as the 30-degree rotation of the brain scan images to be able to see deep in the layers to identify the tumors; scaling of images, that is enlargement and reduction of the scan images so that different sizes of tumors may also be captured by the model. Moreover, we used flipping techniques for horizontal and vertical directions to introduce mirror images of the scans which further helped in identifying symmetrical patterns. Lastly, to improve the recognition of the tumors, we used translation to shift images in multiple directions, making the model robust against small variations in tumor position and improving tumor recognition. These augmentation strategies significantly expanded our training set's diversity, contributing substantially to enhancing the model's capabilities during development.

Contours with Canny Edge Detection: This involved utilizing the Canny algorithm on MRI images to detect significant edge changes that delineate tumors. These detected edges were then processed into contours, facilitating the model's ability to distinguish tumor regions from non-tumor regions. This process enhanced the quality and sharpness of the input data, aiding in more accurate tumor identification and classification.

The image displays a grid of MRI brain scans, illustrating various sections and orientations such as axial, coronal, and sagittal views. The top two rows show standard MRI scans without any modifications. In contrast, the bottom two rows display the same MRI images but with green contours overlaid, indicating the use of Canny Edge Detection. This technique highlights the edges within the images, which can be critical for identifying and analyzing the boundaries of brain tumors or other structures of interest in the scans. This approach is often used in conjunction with deep learning models to improve the accuracy of detecting and diagnosing brain abnormalities.

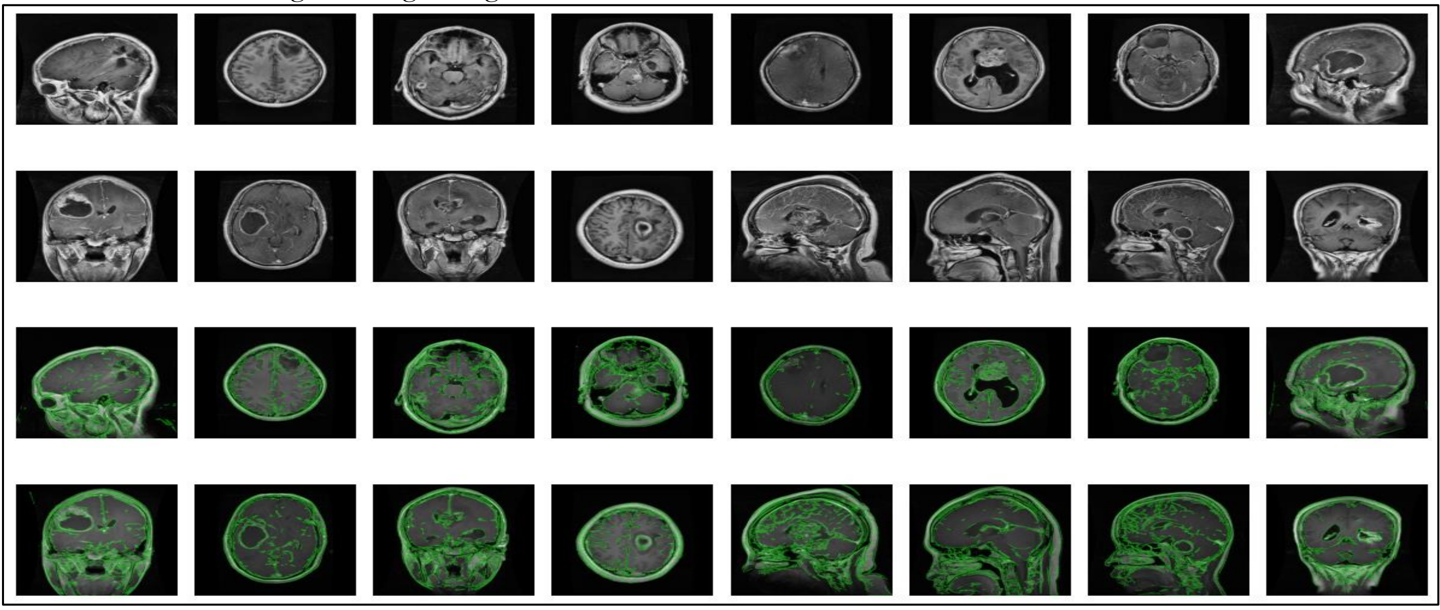

Figure 2: Shows the Applied Canny Techniques.

Proposed EfficientNetB6 Approach:

The proposed approach incorporates the selection of the deep learning architecture EfficientNetB6 which is widely regarded as one of the most precise and efficient models for image classification, to enhance brain tumor classification accuracy [12]. EfficientNetB6 is efficient in handling the intricacies associated with medical imaging data for instance MRI scans of actual brain tumors, in an efficient manner with an optimal utilization of computational resources. Through transfer learning, the model initializes with weights learned from diverse image data and further refines its learning from the already acquired features in extensive datasets. This Sequential model begins with EfficientNetB6 as a staple for feature extraction, then performs global average pooling, applies dropout on the features to avoid overfitting the data, and then feeds this into two fully connected layers for classification. The final dense layer employs SoftMax activation to provide probability rates, indicating the likelihood of the four types of brain tumors.

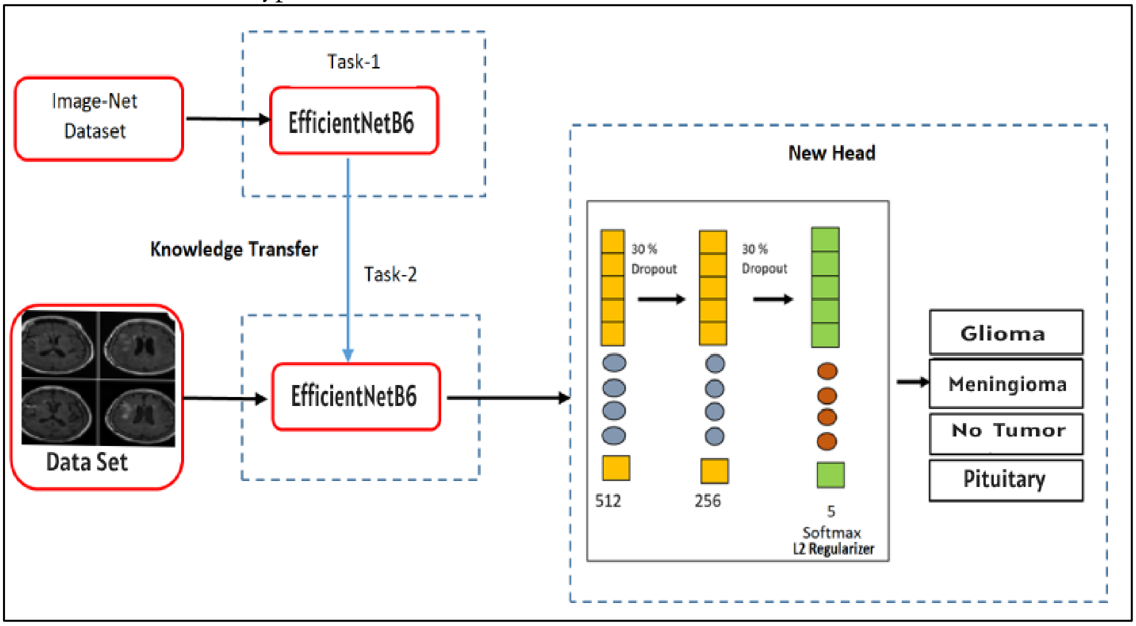

Figure 3: Shows the Architecture of the Proposed Model.

The result of Adamax optimizer with a learning rate of 0. 001 is used to reduce the cross-entropy loss during training time and to pursue a high accuracy in the test as well as in the validation set. The explicative holism of this approach seeks to greatly improve the diagnostic potential of the classification systems for brain tumors, thereby better assisting the medical fraternity with efficient tools to care for them.

Result and Discussion:

Training Environment:

Based on the EfficientNetB6, the model used in the study was designed and trained Google Colab environment, which offers computer GPU for faster computations of deep learning processes. The dataset was provided and stored in Google Drive, which made it easier and convenient to make data handling effective in training. Python served as the primary scripting language, while TensorFlow and Keras were utilized as frameworks for model construction and training. OpenCV performed image preprocessing and Matplotlib provided ways to visualize training performance and outcomes [13]. NumPy supported efficient data manipulation operations. For optimization, the model used the Adamax optimizer with a learning rate set to 0.001, aiming to minimize categorical cross-entropy loss. Testing sets were employed to assess model accuracy and prevent overfitting due to excessive epoch repetitions. This setup was conducive for the fine-tuning of the EfficientNetB6 to serve in the recognition of the brain tumor from the MRI images well, thus facilitating better diagnosis in clinics.

Performance Measurement Metrics:

During the assessment of the proposed EfficientNetB6 model's Accuracy, Precision, and Recall, several metrics were employed. This included accuracy evaluates the overall predictions in the model and their relation to the actual classes. Besides, accuracy and recall were used in evaluating the performance of the detector in accurately predicting the tumorous (positive) cases and its sensitivity to true positive cases. The F1-score used transcends the individual qualities of precision and recall and it offers a broad method of assessing the impact of the classification model of brain tumors. The following equations were used, as shown below:

$$\text{Accuracy} = \frac{\text{Number of Correct Classified Samples}}{\text{Total Number of Samples}} \qquad (5)$$

$$\text{Precision}_{(\text{class}_i)} = \frac{\text{TP}_i}{\text{TP}_i + \text{FP}_i} \qquad (6)$$

$$\text{Recall}_{(\text{class}_i)} = \frac{\text{TP}_i}{\text{TP}_i + \text{FN}_i} \qquad (7)$$

$$\text{F1\_score}_{(\text{class}_i)} = 2 \cdot \frac{\text{Precision}_{(\text{class}_i)} \times \text{Recall}_{(\text{class}_i)}}{\text{Precision}_{(\text{class}_i)} + \text{Recall}_{(\text{class}_i)}} \qquad (9)$$

	precision	recall	f1-score	support
0	1.00	0.99	0.99	150
1	0.98	0.99	0.99	153
2	1.00	1.00	1.00	203
3	0.99	0.99	0.99	150
accuracy			0.99	656
macro avg	0.99	0.99	0.99	656
weighted avg	0.99	0.99	0.99	656

Figure 4: Performance measurements metrics

Results and Analysis:

The EfficientNetB6 employed for classifying brain tumors from MRI images was configured with structured parameters crucial for model performance during training. The model's input shape was defined as 299 x 299, aligning with the architecture of EfficientNetB6. During the training process, a batch size of 32 samples was chosen to accommodate the available memory of the used devices while maintaining computing intensity. To overcome overfitting the condition L2 regularization was incorporated which improved the generalization capacity of the model. The Adamax optimizer was chosen with a learning rate of 0.001 and a momentum of 0.9, facilitating gradient computation and aiding in the vectorization process for smoother convergence of models. The networks were trained for 20 cycles of epochs; while validation after 80 epochs was used to reduce the risk of overfitting the model on training data. These parameters collectively contributed to the model's high accuracy and predictability in identifying brain tumors, highlighting the potential utility of such a model in clinical diagnosis.

Table 1: List of Common Parameters used in model training

Parameter Name	Value
Image Input shape	299 x 299
Batch size	32
Regularizer	L2
Optimizer	ADAMAX
Learning rate	0.001
Momentum	0.9
Epochs	20
Early Stopping	80

Table 2: Performance of the Proposed Model on Test Dataset

Serial No	Metric	Value (%)
1	Accuracy	99.39
2	Precision	100
3	Recall	99.00
4	F1-Score	100

The selected model demonstrated exceptional performance on the test dataset, achieving a test accuracy of 99.39%, specificity of 100%, recall of 99, and an F1-score of 100%. Such metrics emphasize the efficacy of the proposed model in the context of the on-self stability and appositeness of tumor classification with MRI images.

The pre-trained EfficientNetB6 model was then fine-tuned on this dataset. During training, the model's performance was monitored across 20 epochs, with metrics including loss, accuracy, precision, and recall recorded for both training and validation sets.

Comparison with Other SOTA Models:

Comparing the suggested EfficientNetB6 model, with other models recently proposed for the classification of brain tumors based on MRI images, it becomes clear that the EfficientNetB6 possesses superior characteristics. A study was conducted in which an excellent accuracy of 99 percent was recorded in the test run. The precision value was high at 99% accompanied by a high recall rate of 99% consequently meaning that the model possesses a high effectiveness in differentiating the various forms of brain tumor and in rare occasions rarely misclassifying similar brain tumor types. The repetition rate of 1% proved that the model was both precise and able to adequately recall important information to classify documents correctly, resulting in a best F1-score of 99%. In addition to measurements, the EfficientNetB6 efficient network structure and the approach of using transferred weights helped to obtain faster convergence along with good generalization to the unseen dataset during training.

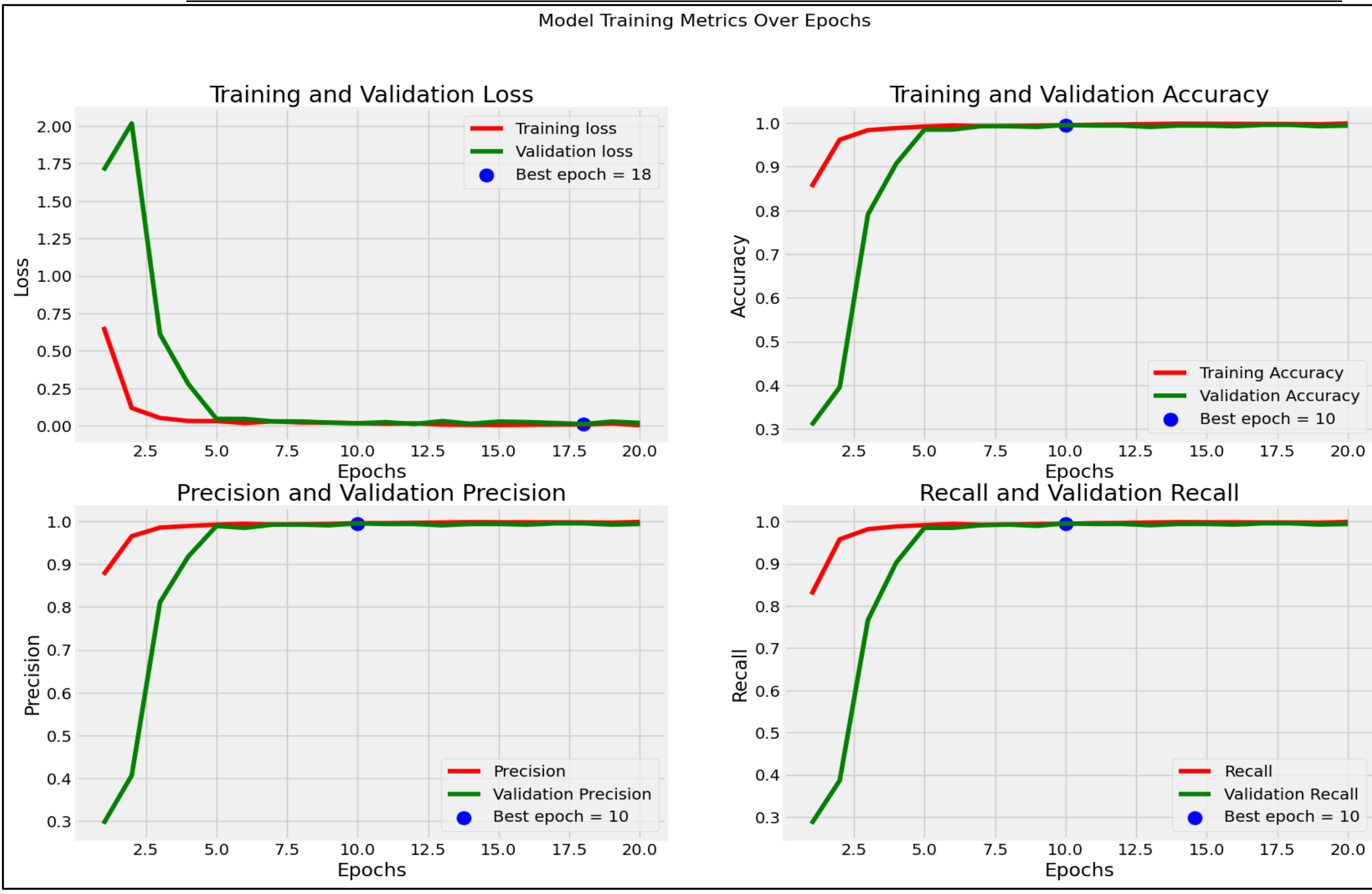

Figure 5: Shows the Performance of the Proposed Model.

Table 3: Number of layers and parameters with accuracy on the test dataset of eye diseases

Model	Training Parameters	No. of Layers	Accuracy (%)
EfficientNetB6	41,255,699	395 + 3 = 398	99.39
EfficientNetB0	4,054,695	237 + 3 = 240	95.00
ResNet50	23,595,908	177 + 3 = 180	97.00

The cross-comparison positions EfficientNetB6 as a highly promising and accurate tool for enhancing brain tumor detection, its potential lies in improving patient outcomes by enhancing doctors' capabilities in medical image analysis, ultimately leading to more effective diagnostic tools.

The findings of this research expedite the development of medical imaging and diagnosis as it showcases how transfer learning and EfficientNetB6 can be used to classify brain tumors. Despite this, the present study has demonstrated high recovery, precision, and recall rates, which may suggest new possibilities for using these techniques to diagnose brain tumors with higher accuracy in clinical practice and identify them at an earlier stage. This advancement demonstrates the use of feature extraction and data augmentation methods toward more efficient ways of coming up with diagnostic frameworks in medical imaging applications.

Prediction on Unseen Images: To validate the credibility of the EfficientNetB6 model for clinical use, its efficacy was tested on unseen MRI scans, demonstrating consistently high accuracy rates across different types of brain tumors. It highlighted the efficacy of the model demonstrating repeatedly high accuracy rates regardless of the types of cancers. First, to test and prove the model efficiency, the MRI image identified a meningioma tumor with a 100% probability. In the second case, it is a victim of a glioma tumor, and as in the first case, the application made a 100% diagnosis. Finally, the model accurately identified a pituitary tumor, specifically assigning it 100 percent probability.

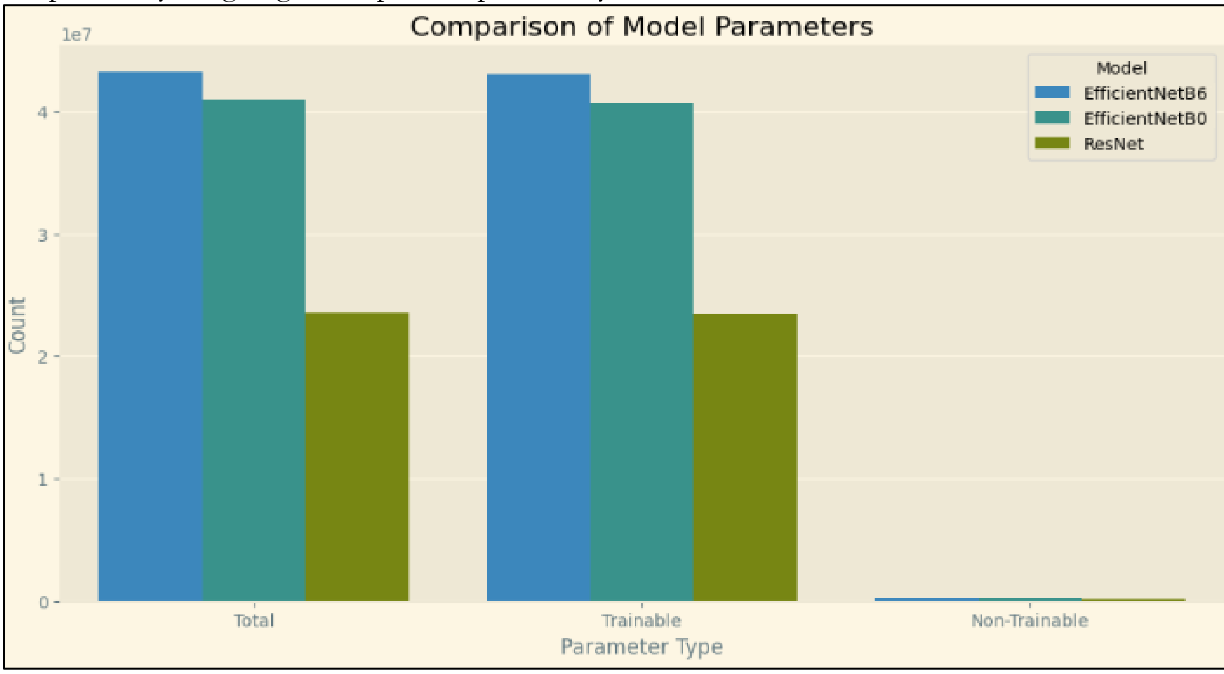

Figure 6: Shows the Comparison of Model Parameters.

These results show that the presented model together with the described training process provides a high level of generalization which means that the accuracy of the model is tremendously high even when it is applied to new data that have not been used at the training. The verification of such predictions by these images serves to build on the credibility of the model, as a means of diagnosing brain tumors more accurately and faster than the current state of practice. The general and especially stable and precise differentiation of various modes of the tumor underlines the model's applicability in the clinics while proposing certain critical advancements in patients' outcomes because of the upgraded diagnostic work.

Discussion:

It is noteworthy that the reviewed research shows that the use of the EfficientNetB6 model enables achieving 99% accuracy for brain tumor classification using MRI images. Precision is 99% recall 99%, and F1-measure of 99%. The following favorable metrics revealed how well grounded the model is establishing itself to be, at least, superior to many other existing models of today: By analyzing the detailed feature of the EfficientNetB6 model, the following factors can be identified as the main factors that influenced the excellent performance of the model: Applying the contours and canny edge detection features increased the quantitative quality of the input image, especially regarding the characteristics of the tumor, which aided the model in correctly classifying the tumors. Moreover, using transfer learning, we were able to use an EfficientNetB6 model that, originally, was trained with a significant quantity of data. We were able to achieve very high accuracy and at the same time have less time for training our model by fine-tuning the above model with the help of our specific brain tumor dataset. It surpassed the conventional methods of machine learning such as Support Vector Machines and Random Forests, and some conventional deep learning networks also. As indicated by the high precision and recall, it means that the model can recognize the various types of brain tumors correctly without instance of over-relying on one algorithm since this would lead to many wrong diagnoses thus affecting the treatment of the affected patients. The consequences of this research are very relevant for medical diagnostics giving possible means to raise the levels of successful prognosis.

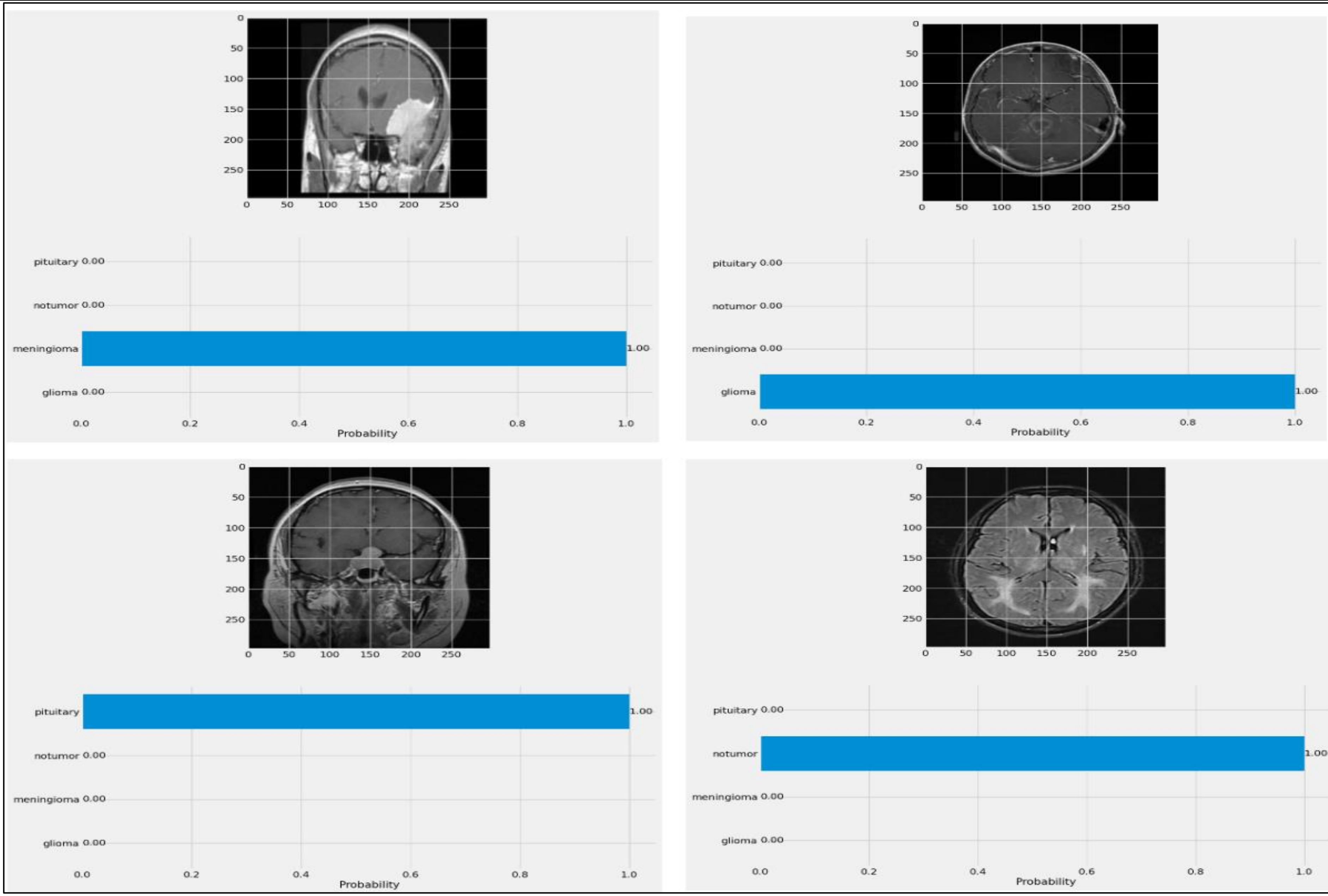

Figure 7: Shows the Prediction Result on Unseen Images

In successive work, one can attempt to collect a larger sample to improve generality and translate this model into a usable software system that can be easily applied in practice.

Conclusion:

Thus, the findings of this study assert that the EfficientNetB6 model performed exceptionally well on the MRI images of the brain to classify between the benign and malignant tumors with a level of accuracy of 99.39% Precision of 99%, and their recall of 99% as well as the F1 score of 99%. Indeed, the model has managed to benefit from following contours and canny edge detection that worked on image enhancement as well as feature enhancement. Transfer learning was used through loading EfficientNetB6 to achieve satisfactory levels of accuracy and model efficiency. From the findings, one can infer that the model can tremendously decrease cases of misdiagnosis and enhance quick and accurate diagnosis of brain tumors improving patient performance.

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