Enhancing Brain Tumor Classification Using Efficientnetb3 And Squeeze-And-Excitation Attention Mechanisms

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ABSTRACT
The presence of brain tumors is one of the major problems for modern medicine, mainly because it is a rather complex phenomenon. Accurate and rapid tumor identification plays an important role in the treatment and subsequent recovery of the patient. It is particularly informative in the detection of brain tumors as an MRI is utilized to yield clear images of the structures present in the brain. However, the assessment of MRI scans by human radiologists is time-consuming, subjective, and prone to various errors that affect the accuracy and timeliness of diagnosis. Considering all these factors, it can be stated that the need for the creation of artificial intelligence-driven diagnostic tools can enhance the speed and accuracy of brain tumor identification. The focus of this paper is thus the development of an automated system for categorizing brain tumors using the EfficientNetB3 deep learning model, which may be improved through the addition of Squeeze and Excitation blocks. The SE Block, an attention mechanism, assists in achieving the feature extraction with a major focus on the significant zones of the image. The proposed model underwent training and testing based on the 7,023 MRI image data. The model met the result of 99.24%, and it showed that it offered 8-10% better performance than present benchmarks. The good performance exhibited here corroborates that deep learning with attention models can enhance the identification of brain tumors to be at par with other benchmark systems. This will be a valuable contribution towards improved medical workflows and overall better healthcare systems for Future Computer-aided Diagnosis Systems (CDS).

KEYWORDS Deep Learning, EfficientNetB3, Squeeze-and-Excitation Block, Brain Tumor, MRI.

1 Introduction

The human brain is the central control unit of the body, performing tasks for cognition, movement, and sensory processing. Any brain abnormality, such as a brain tumor, can have a grave impact on a person's health and quality of life [1]. There are two types of brain cancers: primary tumors develop in the brain, whereas secondary tumors may spread to other parts of the body. It is challenging to diagnose the specific type of brain tumor and the stage of the condition; however, timely identification and classification of a brain tumor help in deciding the best strategy to treat the condition, which can involve surgery, radiation therapy, or chemotherapy. However, the incorrect diagnosis of brain tumors results in serious medical issues that lower both treatment effectiveness and patient survival rates [2]. Brain tumor diagnosis depends on Magnetic Resonance Imaging (MRI) because this medical imaging technique shows detailed soft tissue images through radiation-free investigations [3]. MRI technology provides doctors with visualization of tumors, allowing them to accurately identify their size and shape as well as location to differentiate malignant from benign tumors [4]. The practice of radiologists reading manual MRI scans suffers from long processing times and human mistakes. Examples of healthy brain and tumor MRI scans are illustrated in **Figure 1**

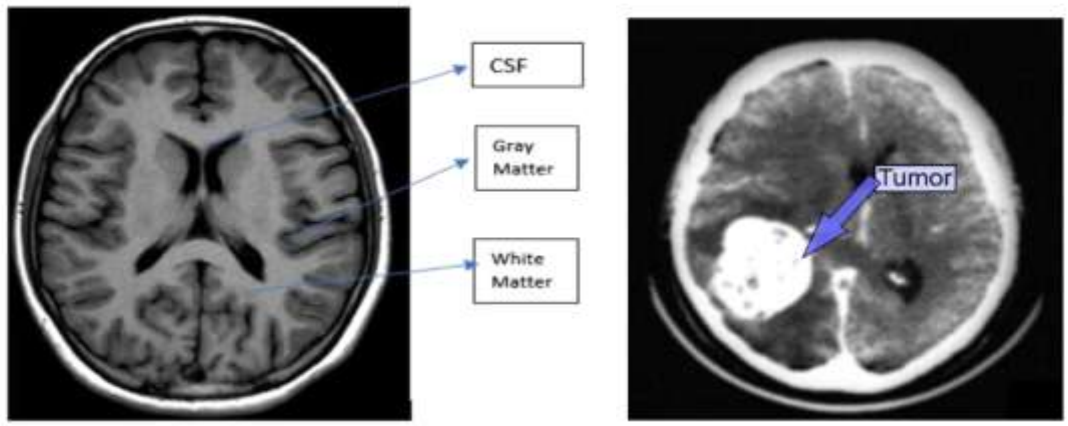


Figure 1: Healthy Brain and Brain Tumor Image [5]

Hence, there is a strong need for brain tumor classification systems to be automated with the help of AI, ensuring enhanced efficiency, consistency, and accuracy in tumor classification [6]–[11]. Recently, deep learning has been proven to change the landscape of various medical imaging applications, and specifically, CNNs have shown excellent performance in the detection, segmentation, and classification of brain tumors. Besides, CNNs can directly learn the features from images without having to go through the process of feature extraction. In the field of deep learning, transfer learning has been widely adopted as a technique where models trained on large databases are adapted for a certain medical purpose. Through this approach, medical practitioners can handle restricted dataset quantities to achieve top performance at lower financial expense. So, the main objective of the study is to develop an extremely accurate automatic system for brain tumor detection and classification with deep learning architectures and attention mechanisms to decrease human dependency. The model is performed on extensive MRI image databases, which proves its performance is better than that of traditional deep learning models. The proposed research presents an advanced deep learning mechanism that employs EfficientNetB3 together with Squeeze-and-Excitation (SE) Block for brain tumor identification. The EfficientNetB3 model demonstrates an ability to maintain an optimal balance between high accuracy levels and efficient operational performance. Through the SE Block mechanism, the model acquires improved attention to relevant image features, which enables it to excel in complex classification tasks. The proposed model achieves better performance than standard CNN architectures by integrating speed improvement alongside accuracy improvement, which makes it an excellent tool for automated brain tumor detection. The main contribution of the study is:

- Presents an improved method based on automated classification of the brain tumor through the EfficientNetB3 model with the squeeze-and-excitation (SE) attention mechanism for better feature extraction.
- Obtains a high accuracy of 99.24%, which is 8-10% superior to other models, proving to be one of the most effective in categorizing brain tumors.
- Creation of a future medical AI-powered diagnostic system that will decrease manual radiological-based evaluations and improve both diagnostic speed and reliability.

The rest of the paper consists of Section 2, which contains related work. The proposed model receives its presentation in the 3rd section. Section 4 includes the experimental findings as well as the details about the simulation setup. A comparative study against the proposed model appears in the 5th section. Section 6 of the paper includes research findings with suggestions for future work.

2 Related Works

Over the past decade, the performance of brain tumor classification has been enhanced by using deep learning approaches. Different approaches have been used for such a task, including CNNs, transfer learning, and ensemble techniques.

Hu et al. [12] figured out that Squeeze-and-Excitation (SE) blocks bring remarkable improvements to the performance of the current state-of-the-art deep architectures with negligible added computation. Meanwhile, Kumar et al. [13] developed a deep convolution neural network for the analysis of brain tumors. The proposed model has reported a high accuracy of 96.3%. Togacar et al. [13] proposed BrainMRNet model achieved 96.05% accuracy in brain MRI image classification. Jain et al. [2] implemented brain tumor automatic classification through VGG-16, ResNet-50, and Inception V3 transfer learning models. A total of 7023 brain MRI tumor images within four classifications have received model applications. ResNet-50 demonstrates superior performance compared to both Inception V3 and VGG-16, according to the experimental analysis results. N. Iriawan et al. [14] applied K-Nearest Neighbors (KNN), SVM, Naive Bayes (NB), Linear Regression Analysis (LR), and Decision Tree (DT) as machine learning models for brain tumor detection. Through machine learning model assessments, the SVM classification method delivered the best results with 85% accuracy. Rasool et al. [15] presented Google-Net as their pre-trained CNN model for feature extraction. The research tested its method with brain MRI images consisting of 1426 glioma tumors, 708 meningioma tumors, 930 pituitary tumors, and 396 normal brain images. Research data indicates that the trained Google-Net model achieved an accuracy level of 93.1%. Tazin et al. [16] used pre-trained deep CNN models: MobileNetV2, VGG19, and InceptionV3. MobileNetV2 achieves higher accuracy levels than other models. Whereas N. A. Zebari et al. [4] developed a Deep Learning Fusion model for the assessment of brain tumors for their classification. To improve model performance, the researchers expand their dataset consisting of 3264 MRI images by using data augmentation techniques. The suggested method achieved 97.05% accuracy in their analysis. Furthermore, Jahan and M. M. Tripathi [3] examined MRI images for brain tumor detection through the use of multi-layer Deep Belief Networks (DBNs). Two different datasets were used on the suggested model. A DBN model successfully diagnosed brain MR images of different tumor types, giving an accuracy rate of 94.28%. D. S. Vinod et al. [6] developed an integrated solution that combines the Self-Organizing Feature Map (SOFM), CNN, and U-Net model to achieve accurate brain tumor segmentation on the BRATS 2020 dataset. The proposed system achieved a 96.7% accuracy level. Meanwhile, a deep learning model VGG-16 employed by Grampurohit et al. [17] performs tumor detection within MRI image content. The researcher examined 253 patient brain MRI scans, which identified 155 tumor cases and 98 cases with no tumors. The research achieved an accuracy rate of 86%. Moreover, Kadrey et al. [11] conducted research to classify brain MRI images by implementing pre-trained deep-learning models VGG16, VGG19, and ResNet-50. The research aims to combine different deep-learning models to achieve the best result for brain tumors. A hybrid model created by [18] joins VGG16 architecture with ResNet-50 to achieve accurate brain tumor classifications. The proposed methodology achieves superior results compared to existing approaches, which assists healthcare professionals in better early identification of brain tumor patients. Pascal et al. [19] deployed a Residual-based MLP (ResMLP) model for brain tumor detection. The Proposed model reached 97.8% accuracy from the analysis. Furthermore, Gayatri et al. [20] obtained 93% accuracy in brain tumor detection by using the VGG-16 model. M. Guler et al. [23] suggested the application of transfer learning methods, including ResNet-50, VGG-16, and Inception v3 models for automatic brain tumor identification and classification. The proposed models applied to 7023 brain tumor MRI images that contained four different classes. The experimental finding demonstrated that ResNet-50 achieved better performance compared to VGG-16 and Inception v3 models, resulting in 95.80% accuracy. Neha et al. [24] introduced an automatic brain tumor classifier that relied on CNN architecture with minimum human support needed for operation. Whereas Mahmud et al [21] demonstrated the use of ResNet-50, VGG16 and InceptionV3 models to detect brain tumors from 3264 MRI images. Moreover, Hassan et al. [16] demonstrated several pre-trained models including Inception-v3, VGG-16 and ResNet-50 for brain MRI scan image identification. The model performed well with small input data while maintaining low complexity levels at 96% for VGG-16, 89% for ResNet-50 and 75% for Inception-V3. The authors in [22] applied CNN-based methods which resulted in 96% accuracy. Moreover, S. Mahajan [23] suggested using VGG-16 to process 700 labeled and preprocessed patient images into brain or non-brain categories. The model demonstrated 94.4% accuracy in its performance. However, there is still the need for models that can be accurate and efficient while at the same time being generalizable. This work addresses these gaps by introducing EfficientNetB3, integrated with the Squeeze-and-Excitation (SE) block, which achieves competitive performance compared with the selected existing approaches.

Table No 1: Summary of related work

Reference	Published Years	Dataset	Model	Accuracy	Limitations
[24]	2020	BRATS	Convolution Neural Network (CNN)	96.30%	Computationally intensive; not optimized for diverse tumor types.
[25]	2020	MRI images (3064 images)	Convolution Neural Network (CNN)	96.56%	Overfitting potential without extensive data augmentation.
[15]	2022	MRI 3460 images	Google-Net	93.1%	Lower accuracy compared to other models; limited feature representation.
[16]	2021	MRI 4600 images	MobileNetV2 InceptionV3 VGG19	92% 91% 88%	Moderate accuracy is not ideal for highly complex datasets.
[4]	2024	MRI 3264 images	ResNet50 VGG16	96.95% 93.90%	Complexity increases with deeper networks; VGG16 is computationally intensive.
[2]	2023	MRI 7023 images	VGG-16 ResNet-50 Inception v3	91.67% 97.65% 97.36	Inception v3 and VGG-16 lag in accuracy compared to ResNet-50.

From the results in **Table 1**, there is a research gap in developing better classification models for brain tumors. Even though the ResNet-50, VGG-16, and Inception V3 have exhibited relatively high accuracy, there are certain drawbacks as far as precision, recall values, and generalization capacity. Most of these models can sometimes misclassify between different types of tumors, which is evident in some of the above models. However, existing architectures of conventional CNNs fail to incorporate a method for focusing on these significant features in MRI images, which mainly hampers its classification accuracy. To overcome these issues, the proposed study combines the EfficientNetB3 model with Squeeze-and-Excitation (SE) blocks to boost feature extraction and increase the model's attention to the tumor regions of interest. This innovative combination results in a high performance of 99.24%, in comparison with the existing achievements.

3 Methodology

Over the last few years, deep neural networks have been applied to identifying diseases autonomously. This study utilizes EfficientNetB3 and Squeeze-and-Excitation (SE) attention Mechanisms for the classification of brain tumors in medical images. The proposed methodology employs a well-organized step-by-step approach that guarantees the detection and categorization of the tumor from MRI images. The architecture of the proposed model is depicted in Figure 2.

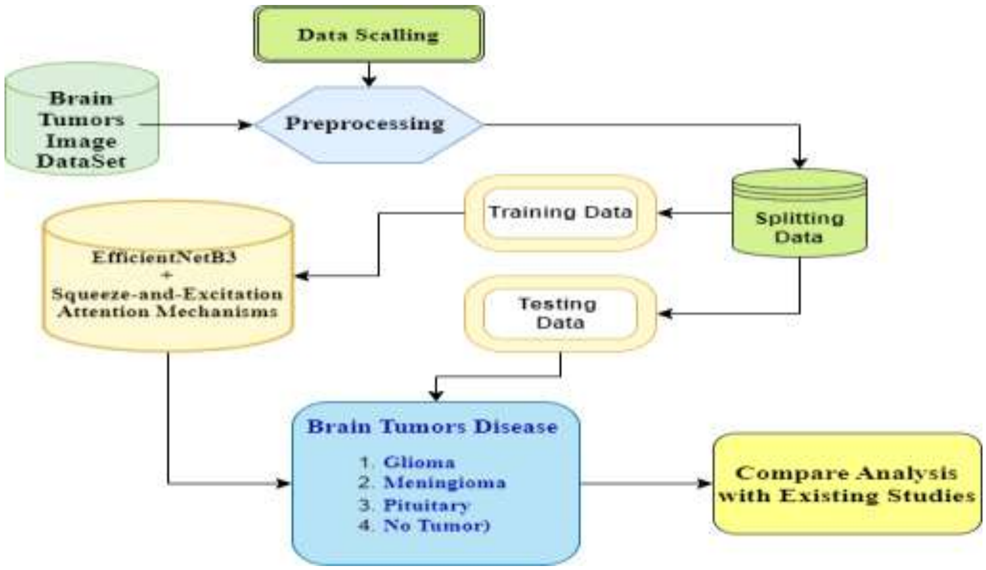


Figure 2: Proposed Model for Brain Tumor Detection

The first step of this study will be the selection of MRI images from the Brain MRI Dataset. A total number of 7023 images will be used in the proposed methodology. The dataset offers a diverse and quite extensive set of brain MRI scans, which are essential for building a reliable and accurate deep learning model to classify between tumor and non-tumor cases. The dataset will be split into four different classes, namely Glioma, Meningioma, Pituitary Tumor, and No Tumor.
The dataset's class distribution is illustrated in Figure 3.

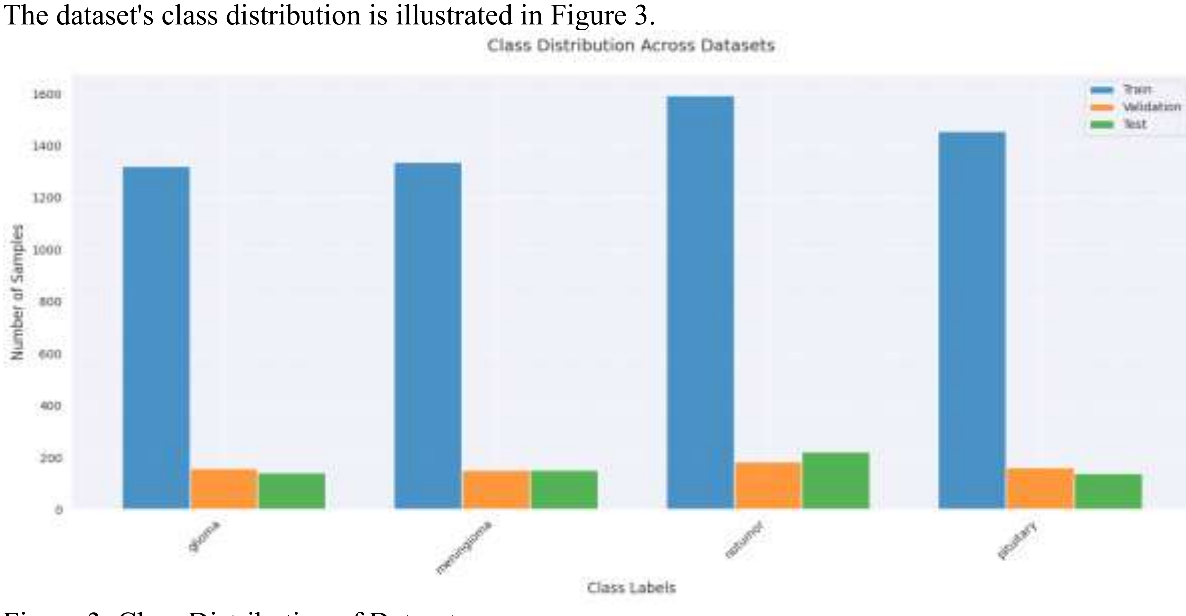


Figure 3: Class Distribution of Dataset

Glioma tumors develop from glial cells located in the brain or spinal cord and represent the most dynamic and difficult-to-treat cancer types. The protective membranes named meninges form Meningioma tumors, which require exact medical intervention because they show variable severity. The pituitary gland serves as the source of tumors that disrupt hormone control and trigger various medical difficulties. Normal MRI scans that fall under the No Tumor category serve as essential reference points for diagnosing healthy brain tissue against pathological conditions.

Another important procedure to be performed before training is the preprocessing of an image, which brings additional quality to data and provides consistency. All images undergo resizing to 224 × 224 pixels to maintain a standard input format throughout the model's system. During training, the model needs normalized pixel scaling to achieve efficient convergence.
After preprocessing, data will be split into three sections: Training at 80%, Validation at 10%, and Testing at 10% to support balanced training and reliable evaluation. The training, validation, and testing data are presented in Figure 4.

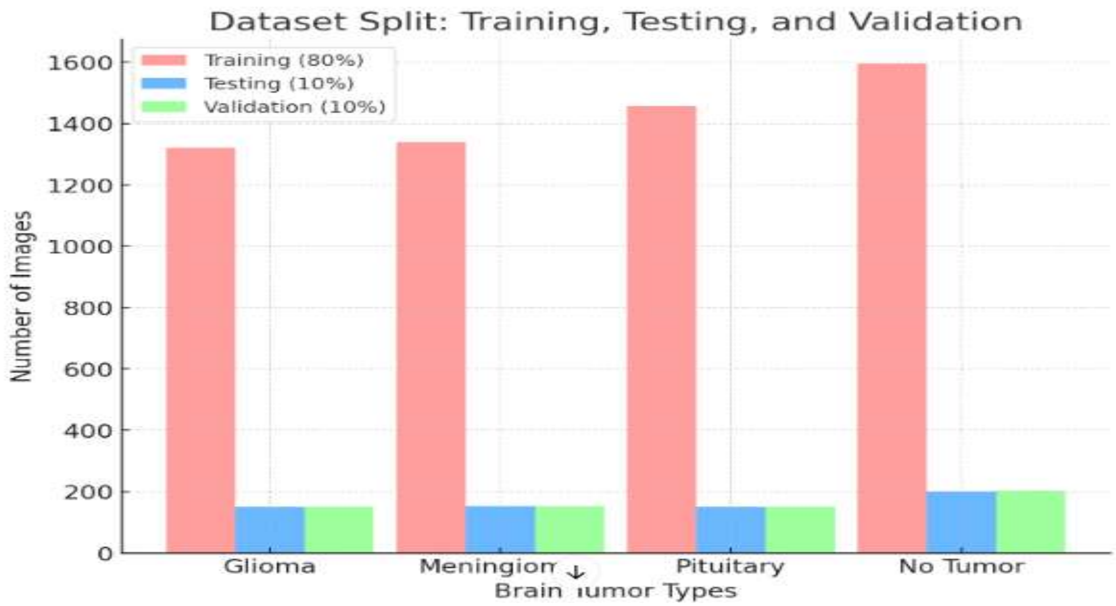


Figure 4: Training, Testing, and Validation Data for Proposed Model

The proposed method utilizes EfficientNetB3 architecture as its fundamental model framework. The CNN architecture EfficientNetB3 delivers high accuracy standards while requiring fewer parameters than other traditional CNN approaches. In addition to this, EfficientNetB3 uses compound scaling, which enhances depth, width, and optimal resolution to achieve higher efficiency and accuracy. This makes it ideal for use where computational resources must be minimized, especially when they are being used in a medical application. To increase the extraction of features, the Squeeze-and-Excitation (SE) Block is added to the given model. SE Block is an operation that enables focusing on the most relevant aspects of the image and, thus, helps to increase its classification accuracy. The SE block has two main operational stages, known as squeeze and excitation. The squeeze layer is used to analyze the feature map dimension with a global average pooling layer, thus retaining only a few of the most important aspects. This step helps provide a solid representation of the image input while maintaining some of the important characteristics. During the excitation phase, the fully connected layers and the activation functions re-scale the channel-wise feature responses. After adding the SE block, the model utilizes the Adamax optimizer, which integrates Adam's strengths and offers additional stability through the infinity norm. In deep learning applications, this optimizer proves to be very effective because of faster convergence and good generalization. The training process has 30 epochs with a learning rate of 0.001 to prevent the model from overfitting while learning well. The model keeps refining its parameters throughout training to reach peak performance as much as possible.
The performance of the proposed model was evaluated using a confusion matrix and standard classification metrics, including accuracy, precision, recall, and F1-score.The confusion matrix [26] combines four distinct values, True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP), to create distinct matrices. Several performance metrics that can be used to evaluate models using the confusion matrix are discussed below.

The accuracy represents the ratio of correctly classified data points to the total number of data points [27]. Accuracy is mathematically defined as follows.

$$\text{Accuracy} = (TP+TN) / (TP+TN+FP+FN) \quad (1)$$

Precision is expressed in terms of the ratio of true positive predictions in comparison to their total number of positive predictions [28]. The following relationship describes precision.

$$\text{Precision} = TP / (TP+FP) \quad (2)$$

The recall is the number of predictions that were true out of all those that were positive [29], given by:

$$\text{Recall} = TP / (TP+FN) \quad (3)$$

Finally, the F1-Score is the harmonic mean of the recall and the precision, as suggested in [30]. Mathematically,

$$\text{F1-score} = (2*(\text{Precision}*\text{Recall})) / ((\text{Precision}+ \text{Recall})) \quad (4)$$

4 Results & Discussion

This chapter describes the performance of the EfficientNetB3 model, which contains Squeeze-and-Excitation attention blocks, in classifying brain cancers from MRI data. The study evaluates the model's effectiveness utilizing accuracy, precision, recall, F1-score, confusion matrix, and receiver operating characteristic (ROC) curve. The performance of the suggested approach is also compared to existing **models to demonstrate their superiority.**

Table 2 provides a full depiction of this study's Accuracy, Precision, Recall, and F1-Score characteristics. The confusion matrix in Figure 5 shows how EfficientNetB3 classifies different groups. The visual representation shows the model classification output for the glioma, meningioma, pituitary, and no tumor classifications. The model has minimum classification errors for all labels while maintaining an unusually good discriminate capability between tumor kinds. Figure 6 depicts how training loss patterns evolve with each epoch. After putting training data into the model to begin operation, the error rate gradually drops to its minimum. The observed loss reduction illustrates consistent data learning, since result deviations continue to decrease until the model performs consistently. Figure 7 shows the accuracy results from the training and validation phases. The accuracy curves from the training and validation sets are positioned together, indicating that the model performs equally well with new and current information.

Table 2: **Classification Report for EfficientNetB3 with Squeeze-and-Excitation Block**

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Glioma	1.00	0.99	0.99	139
Meningioma	0.99	0.99	0.99	153
No Tumor	0.99	1.00	1.00	222
Pituitary	0.99	0.99	0.99	142
Average	0.99	0.99	0.99	656
Accuracy	99.24 %			

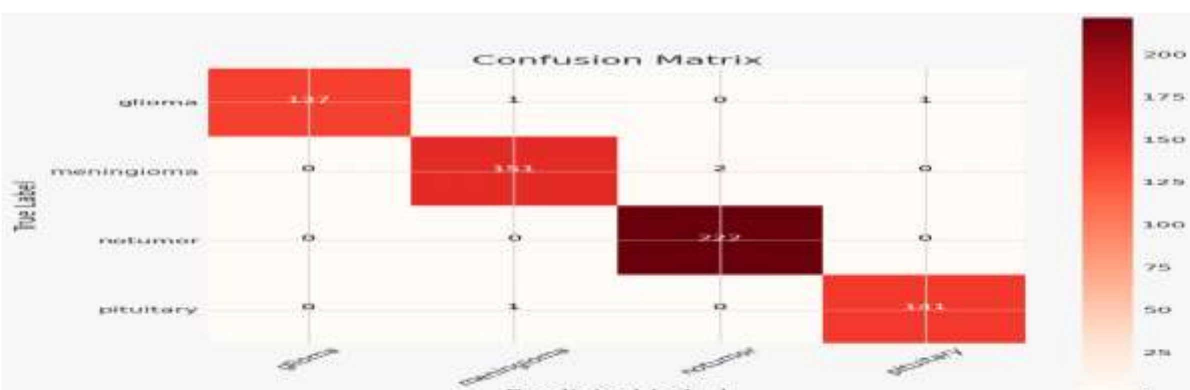
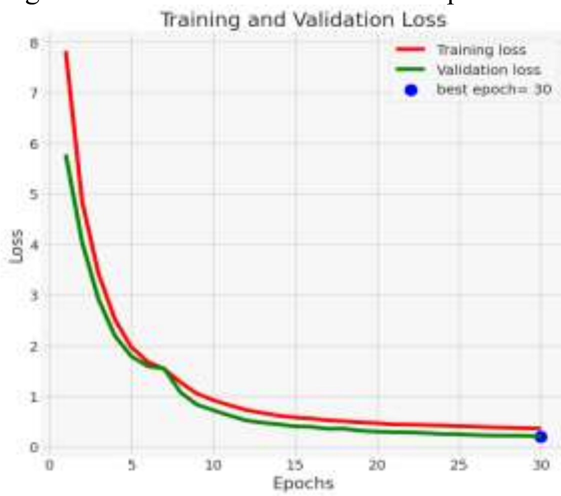


Figure 5: Confusion Matrix of the Proposed Model



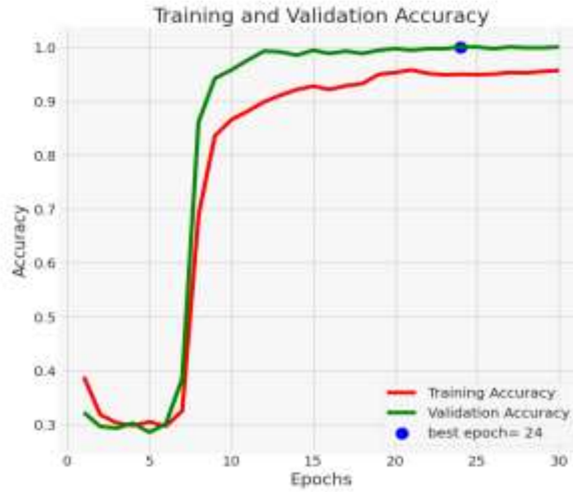


Figure 6: Training and Validation Loss

Figure 7: Training and Validation Accuracy

Moreover, the ROC Curve of the proposed model is presented in **Figure 8**.

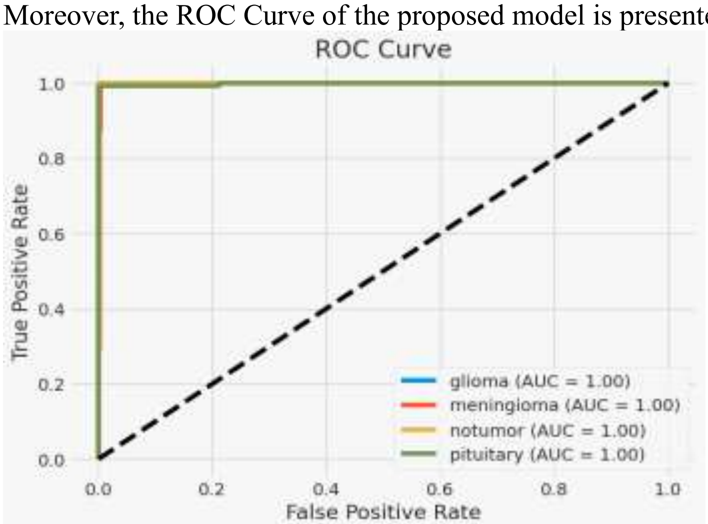


Figure 8: ROC Curve

Figure 8 presents the one-vs-rest ROC curves for the four classes: glioma, meningioma, no tumor, and pituitary. The proposed model achieved an AUC of 1.00 for each class, indicating excellent class separability based on the predicted probability scores. However, the confusion matrix shows a small number of classification errors, demonstrating that perfect AUC does not necessarily imply zero misclassification at the selected decision threshold.

5 Analysis of the Proposed Model with Existing Studies

A comparison with state-of-the-art models was made to validate the performance of the suggested technique. The suggested EfficientNetB3 with SE Block model surpasses existing models in accuracy, precision, and recall. Table 3 presents a comparative analysis.

Table 3: Comparison of Proposed Model with Similar Studies

Model	Accuracy	Precision	Recall	Reference
MobileNetV2	92%	92%	92%	[16]
VGG-16	96%	96%	96%	[2]
ResNet-50	97.65%	97%	97%	[2]

InceptionV3	95.80%	95%	95%	[2]
Proposed Model (EfficientNetB3 with SE Block)	99.24%	99%	99%	

This paper introduced the incorporation of an improved deep learning model named EfficientNetB3 with a Squeeze-and-Excitation (SE) Attention mechanism and learned that the enhancement was very significant compared to the traditional deep learning frameworks, especially when dealing with medical images. It has a slightly higher accuracy of 99.24% and thus performs better than ResNet-50 with 97.65% accuracy, VGG-16 with 96% accuracy, and InceptionV3 architecture of 95.80%. It is an important improvement, especially in a medical field where minor improvements in accuracy can immensely improve diagnostic reliability and patient outcomes. SE Attention takes this step forward by adaptively re-normalizing the feature responses in the channel dimension, focusing only on diagnostically discriminative patterns to improve tumor identification and decrease misclassification.

6 Conclusion and Future Work

The research developed an advanced brain tumor classification system by incorporating EfficientNetB3 with a Squeeze-and-Excitation (SE) attention mechanism. The newly proposed system achieved outstanding results through its 99.24% accuracy, which bested the performance of ResNet-50, VGG-16, and InceptionV3 models. The SE attention mechanism provided essential functionality to improve feature extraction because it focused on important regions in MRI images, which resulted in a substantial reduction in misclassification. The exceptional performance of this model highlights its potential for helping in accurate brain tumor diagnosis through automated medical systems that improve patient treatment workflows.

Future study will focus on improving models for assessing clinical efficacy by testing across various multi-center datasets. The objective is to achieve extensive clinical adoption by analyzing outcomes across various imaging modalities across diverse patients and populations. Subsequently, supplementary imaging techniques like CT or PET scans may be employed and incorporated to enhance diagnostic insights, utilizing multi-modal data fusion to refine tumor characterization and classification precision. Furthermore, enhancing model interpretability through XAI techniques such as attention maps or feature importance maps may elucidate the model's outcomes for practitioners, thereby bolstering their confidence in AI within healthcare. In addition to these modifications, the integration of the model into clinical decision support systems is the most efficacious method of application, as it equips radiologists with AI capabilities to precisely evaluate a tumor, devise treatment plans, and predict outcomes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authorship contribution

All authors have contributed equally to this work.

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Data availability

The data used to support the findings of this study are available from the corresponding authors upon request.

References

[1] S. Anantharajan, S. Gunasekaran, T. Subramanian, and V. R, “MRI brain tumor detection using deep learning and machine learning approaches,” Meas. Sensors, vol. 31, no. January 2023, p. 101026, 2024, doi: 10.1016/j.measen.2024.101026.

[2] J. Jain, M. Kubadia, M. Mangla, and P. Tawde, “Comparison of Transfer Learning Techniques to Classify Brain Tumours Using MRI Images †,” Eng. Proc., vol. 59, no. 1, 2023, doi: 10.3390/engproc2023059144.

[3] R. Jahan and M. M. Tripathi, "Detection of Brain Tumour in MRI Images using Deep Belief Network (DBN)," J. Adv. Res. Appl. Sci. Eng. Technol., vol. 41, no. 1, pp. 154–167, 2024, doi: 10.37934/araset.41.1.154167.
[4] N. A. Zebari et al., "A deep learning fusion model for accurate classification of brain tumours in Magnetic Resonance images," CAAI Trans. Intell. Technol., no. June 2023, 2024, doi: 10.1049/cit2.12276.
[5] R. Kaifi, "A Review of Recent Advances in Brain Tumor Diagnosis Based on AI-Based Classification," Diagnostics, vol. 13, no. 18, 2023, doi: 10.3390/diagnostics13183007.
[6] D. S. Vinod, S. P. S. Prakash, H. Alsalman, A. Y. Muaad, and M. B. Bin Heyat, "Ensemble Technique for Brain Tumor Patient Survival Prediction," IEEE Access, vol. 12, no. February, pp. 19285–19298, 2024, doi: 10.1109/ACCESS.2024.3360086.
[7] N. Varuna Shree and T. N. R. Kumar, "Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network," Brain Informatics, vol. 5, no. 1, pp. 23–30, 2018, doi: 10.1007/s40708-017-0075-5.
[8] H. Kibriya, R. Amin, J. Kim, M. Nawaz, and R. Gantassi, "A Novel Approach for Brain Tumor Classification Using an Ensemble of Deep and Hand-Crafted Features," Sensors, vol. 23, no. 10, 2023, doi: 10.3390/s23104693.
[9] Z. H. N. Al-Azzwi and A. N. Nazarov, "Brain Tumor Classification based on Improved Stacked Ensemble Deep Learning Methods," Asian Pacific J. Cancer Prev., vol. 24, no. 6, pp. 2141–2148, 2023, doi: 10.31557/APJCP.2023.24.6.2141.
[10] A. Veeramuthu, S. Meenakshi, G. Mathivanan, and K. Kotecha, "MRI Brain Tumor Image Classification Using a Combined Feature and Image-Based Classifier," vol. 13, no. March, pp. 1–12, 2022, doi: 10.3389/fpsyg.2022.848784.
[11] P. Gao, W. Shan, and Y. Guo, "Development and validation of a deep learning model for brain tumor diagnosis and classification using magnetic resonance imaging," JAMA Netw. Open, vol. 5, no. 8, 2022, doi: 10.1001/jamanetworkopen.2022.25608.
[12] J. Hu, "Squeeze-and-Excitation_Networks_CVPR_2018_paper.pdf," Cvpr, pp. 7132–7141, 2018, [Online]. Available: http://openaccess.thecvf.com/content_cvpr_2018/html/Hu_Squeeze-and-Excitation_Networks_CVPR_2018_paper.html
[13] M. Toğaçar, B. Ergen, and Z. Cömert, "BrainMRNet: Brain tumor detection using magnetic resonance images with a novel convolutional neural network model," Med. Hypotheses, vol. 134, 2020.
[14] N. Iriawan et al., "YOLO-UNet Architecture for Detecting and Segmenting the Localized MRI Brain Tumor Image," Appl. Comput. Intell. Soft Comput., vol. 2024, 2024, doi: 10.1155/2024/3819801.
[15] M. Rasool et al., "A Hybrid Deep Learning Model for Brain Tumour Classification," Entropy, vol. 24, no. 6, 2022, doi: 10.3390/e24060799.
[16] T. Tazin et al., "A Robust and Novel Approach for Brain Tumor Classification Using Convolutional Neural Network," Comput. Intell. Neurosci., vol. 2021, 2021, doi: 10.1155/2021/2392395.
[17] S. Grampurohit, V. Shalavadi, V. R. Dhotargavi, M. Kudari, and S. Jolad, "Brain Tumor Detection Using Deep Learning Models," Proc. - 2020 IEEE India Counc. Int. Subsections Conf. INDISCON 2020, pp. 129–134, 2020, doi: 10.1109/INDISCON50162.2020.00037.
[18] V. K. Dhakshnamurthy, M. Govindan, K. Sreerangan, M. D. Nagarajan, and A. Thomas, "Brain Tumor Detection and Classification Using Transfer Learning Models," Eng. Proc., vol. 62, no. 1, 2024, doi: 10.3390/engproc2024062001.
[19] I. Pacal, "A novel Swin transformer approach utilizing residual multi-layer perceptron for diagnosing brain tumors in MRI images," Int. J. Mach. Learn. Cybern., no. 0123456789, 2024, doi: 10.1007/s13042-024-02110-w.
[20] P. Gayathri, A. Dhavileswarapu, S. Ibrahim, R. Paul, and R. Gupta, "Exploring the Potential of VGG-16 Architecture for Accurate Brain Tumor Detection Using Deep Learning Related Work," no. April 2023, pp. 1–10, doi: 10.57159/gadl.jcmm.2.2.23056.1.
[21] M. M. and A. A. Md Ishtyaq Mahmud, "A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks," Algorithms, pp. 1–19, 2023.

[22] B. A. Mohammed and M. S. Al-Ani, “An efficient approach to diagnose brain tumors through deep CNN,” Math. Biosci. Eng., vol. 18, no. 1, pp. 851–867, 2021, doi: 10.3934/MBE.2021045.
[23] S. Mahajan, “An E cient Deep Learning Technique for Brain Abnormality Detection Using MRI Images,” 2024.
[24] S. Kumar and D. P. Mankame, “Optimization driven Deep Convolution Neural Network for brain tumor classification,” Biocybern. Biomed. Eng., vol. 40, no. 3, pp. 1190–1204, 2020, doi: 10.1016/j.bbe.2020.05.009.
[25] M. M. Badža and M. C. Barjaktarović, “Classification of brain tumors from mri images using a convolutional neural network,” Appl. Sci., vol. 10, no. 6, 2020, doi: 10.3390/app10061999.
[26] A. Tripathy, A. Agrawal, and S. K. Rath, “Classification of sentiment reviews using n-gram machine learning approach,” Expert Syst. Appl., vol. 57, no. October 2017, pp. 117–126, 2016, doi: 10.1016/j.eswa.2016.03.028.
[27] P. Lin, K. Ye, and C. Z. Xu, “Dynamic network anomaly detection system by using deep learning techniques,” Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 11513 LNCS, no. November, pp. 161–176, 2019, doi: 10.1007/978-3-030-23502-4_12.
[28] S. A. Ludwig, “Intrusion detection of multiple attack classes using a deep neural net ensemble,” 2017 IEEE Symp. Ser. Comput. Intell. SSCI 2017 - Proc., vol. 2018-Janua, pp. 1–7, 2018, doi: 10.1109/SSCI.2017.8280825.
[29] B. Roy and H. Cheung, “A Deep Learning Approach for Intrusion Detection in Internet of Things using Bi-Directional Long Short-Term Memory Recurrent Neural Network,” in 28th Int. Telecommun. Networks Appl. Conf. ITNAC 2018, 2019, pp. 1–6.
[30] S. Moraboena, G. Ketepalli, and P. Ragam, “A deep learning approach to network intrusion detection using deep autoencoder,” Rev. d’Intelligence Artif., vol. 34, no. 4, pp. 457–463, 2020, doi: 10.18280/ria.340410.