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Enhanced Transfer Learning with Attention Recalibration for Brain Tumor Classification on MRI Images

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Abstract:

The accurate and timely identification of brain tumors in MRI scans remains a complex task due to tumor variability and limitations of manual analysis, which has led to the development of automated intelligent systems. This work suggests an attention-boosted deep learning model that combines transfer learning via the pretrained EfficientNetB0 and Squeeze-and-Excitation (SE) attention mechanism for enhanced feature representation. The training dataset comprises 3264 brain MRI images spanning four classes: glioma meningioma pituitary tumor, and absence of tumor. The image preprocessing steps include resizing, normalization, and label encoding. The proposed architecture fuses effective feature extraction, attention-driven recalibration, and a regularized classification head for better results. A systematic strategy for model development with early stopping and adaptive learning rate fine-tuning is implemented for reliable convergence. The results demonstrate that our proposed framework yields a validation accuracy of 97.05% and a validation loss of 0.0959 at the optimal epoch. In addition, the model surpasses traditional models like MobileNetV1 and DenseNet121 as well as recently developed hybrid models. Moreover, this study reveals that the use of attention mechanisms significantly enhances classification performance while keeping the computational costs low.

Keywords: Brain Tumor Classification, MRI, Deep Learning, Transfer Learning, Attention Mechanism, EfficientNetB0.

Introduction

Brain tumors form abnormal growth of cells in the brain. These tumors grow in many ways and become an even larger threat to the health of the patient in question. The world health organization classified brain tumors into low grade or high-grade tumors based on the growing aggressiveness and malignancy of the tumor (Wong *et al.*, 2025). Recent estimates indicate that approximately 1.3 million Americans are living with a brain tumor, with 108,810 new primary brain tumor diagnoses and 18,350 deaths from malignant brain tumors expected in 2026 (National Brain Tumor Society, 2026), highlighting the importance of early detection and accurate classification to improve treatment outcomes and survival rates (Abdel-Basset *et al.*, 2023).

Magnetic resonance imaging (MRI) stands out as it offers a very detailed look into the tumor's size, position, and its inner composition (Aboussaleh *et al.*, 2024). Nevertheless, the human analysis of MRI scans is not only labor-intensive but also the results can vary from one observer to another, thereby potentially impacting the reliability of the diagnosis and the consequent clinical decisions (Aggarwal *et al.*, 2023). This drawback makes us realize the importance of having smart, automated systems that can assist the work of the radiologists.

Deep learning (DL), which is one of the main areas of artificial intelligence (AI), has been able to tackle very difficult image analysis problems, which is especially true in medical imaging (Lamba, 2025). For brain tumor diagnosis, DL methods, in particular convolutional neural networks (CNNs), have the ability to extract multilevel features from MRI, thereby achieving highly accurate and fast classification (Neamah *et al.*, 2023). Back in the day (Rasool & Bhat, 2025), radiomics approaches used to depend on handcrafted features and machine learning models, but these techniques are constrained by feature dependency and also need domain expertise (Azeez & Abdulazez, 2025). On the other hand, CNN-based DL models fine-tune feature extraction while training and therefore can grasp even very fine patterns leading to better prediction results (Missaoui *et al.*, 2025).

Although DL-based systems have achieved considerable success, several challenges are still impeding its application for brain tumor classification,

such as feature redundancy, relatively small number of training data and inability to identify important regions of the tumor (Das & Goswami, 2024). These challenges can severely limit the performance of the systems and the ability to generalize to unseen data.

To compensate for these limitations, this project has adopted a transfer learning-based approach by utilizing the rich information captured by pretrained models to extract discriminative and generalized features from MRI data, which effectively reduces the burden of data annotation and enhances the training efficiency. An attention recalibration module is also proposed in order to recurrently adjust the extracted feature maps which learn more dominant information that allows the network to focus on the signature patterns related to differentiation between classes in a more robust way, thus enabling the model to better suppress background interference.

Related Work

Classifying brain tumors has seen significant developments using MRI in combination with deep learning and transfer learning (TL) techniques. There is still substantial room for improvement for generalization, precision, and feature representation in brain tumor classification. Early work (Srinivas *et al.*, 2022) demonstrated the effectiveness of pretrained CNNs, particularly VGG-16, ResNet-50, and InceptionV3, on limited MRI datasets, where VGG-16 achieved superior performance. Likewise, the study (Alanazi *et al.*, 2022) showed that fine-tuned transfer learning CNN models resulted in a high classification accuracy (up to 95.75%); an example of a highly beneficial optimization of CNN model classification results. The study (Mahmoud *et al.*, 2023) further enhanced performance by combining multiple pretrained architectures with Aquila Optimization (AQO), where VGG-19 achieved the best results, indicating the importance of model optimization techniques.

According to the study (Ait Amou *et al.*, 2022), a CNN framework optimized with Bayesian Optimization (BO) achieved 98.70% accuracy. With the emphasis of automated hyperparameter tuning, the framework showed notable improvements over several standard transfer learning models. The study (Rasheed *et al.*, 2023), reported a 97.84% accuracy by combining image enhancement techniques such as CLAHE and



Gaussian-blur sharpening with CNN models. The study (Shah, 2024), InceptionV3 based CNN with extensive preprocessing and 5-fold cross-validation on a dataset of 7023 images, showed robust results with limited interpretability.

Further studies have reported more advanced architectures. The study (Aloraini *et al.*, 2023) reported a high computational cost, a hybrid architecture of CNN and Vision Transformer (ViT), with local and global contexts, respectively. The study (Srinivasan *et al.*, 2024) created optimized CNN architectures for tumor detection, classification, and grading with a grid search optimization approach and reported high accuracy. However, no external clinical validation was provided. The study (Suryawanshi & Patil, 2024) showed improved classification performance by using a hybrid approach of CNN and VGG19 based features. However, this work was limited by high computational complexity and low interpretability of the model. The study (Disci *et al.*, 2025) analyzed the performance of pre-trained CNNs of Xception, DenseNet121, and ResNet50, and reported Xception with the best accuracy of 98.73%. However, it had limited dataset diversity and no external validation. The study (Afroj *et al.*, 2025) reported a hyperparameter optimized framework with feature fusion of a highly performant, lightweight, and hybrid architecture of MobileNetV1 and DenseNet called MobDenseNet, with excellent multi-class classification performance.

Table 1 highlights important facets of related works, such as datasets, used technologies, contributions, and limitations.

Table 1: Summary of related brain tumor classification studies.

Ref.	Dataset	Technologies	Main Contribution	Main Limitation
(Srinivas <i>et al.</i> , 2022)	233 MRI images	VGG-16, ResNet-50, InceptionV3	VGG-16 showed best transfer learning performance	Limited dataset size
(Alanazi <i>et al.</i> , 2022)	MRI tumor dataset	CNN, Transfer Learning	Fine-tuned CNN improved classification accuracy	Limited architectural diversity
(Mahmoud <i>et al.</i> , 2023)	MRI tumor dataset	VGG-16, VGG-19, InceptionV3, AQO	AQO-optimized VGG-19 achieved best results	High optimization complexity
(Ait Amou <i>et al.</i> , 2022)	CE-MRI (3064 images)	CNN, Bayesian Optimization	BO-based CNN outperformed pretrained models	Class imbalance issues
(Rasheed <i>et al.</i> , 2023)	Figshare, SARTAJ, BR35H	CNN, CLAHE, Gaussian blur enhancement	Image enhancement improved classification accuracy	Sensitive to preprocessing variations
(Shah, 2024)	Figshare (7023 images)	InceptionV3, CNN, 5-fold CV	Strong performance with large-scale validation	Limited interpretability
(Aloraini <i>et al.</i> , 2023)	BraTS 2018, Figshare	CNN, Vision Transformer (ViT)	CNN-Transformer fusion improved feature learning	High computational cost
(Srinivasan <i>et al.</i> , 2024)	Figshare, REMBRANDT	Optimized CNN, Grid Search	High accuracy in detection, classification, grading	No external clinical validation
(Suryawanshi & Patil, 2024)	BraTS, Sartaj datasets	CNN, VGG19, SVM	Hybrid CNN-SVM improved classification performance	High computational cost, low interpretability
(Disci <i>et al.</i> , 2025)	7023 MRI images	Xception, DenseNet121, ResNet50	Xception achieved highest accuracy (98.73%)	Limited dataset diversity
(Afroj <i>et al.</i> , 2025)	MRI datasets	MobDenseNet (MobileNetV1 + DenseNet)	Lightweight hybrid model with strong performance	Limited generalization across datasets



After surveying the literature, it is apparent that deep learning and transfer learning-based brain tumor classifications have made significant advances. However, most of the works suffer from several drawbacks, such as feature redundancy, low generalization capability across datasets, and high sensitivity to data preprocessing, along with insufficient consideration for differentiating tumor regions (e.g., meningioma vs. glioma). This makes a strong case for developing novel frameworks that allow for advanced feature representation geared toward clinically relevant tumor regions.

Methodology

The proposed approach introduces a DL framework to automatically classify brain tumors from MRI scans. It combines transfer learning and attention mechanisms to improve feature representation and classification accuracy. As shown in Figure 1, the system is designed to extract features efficiently and achieve high performance across multiple classes consistently.

The implemented system development platform involves a cloud-based environment of Google Colab which lends GPU that is an accelerating deep learning model training support. Moreover, development is made in Python as it is an easy language and the ecosystem for artificial intelligence applications is very strong. Specifically, ngx. supports the building and training of deep learning models; Together with NumPy and Matplotlib, TensorFlow and Keras are main libraries used for implementing the model.

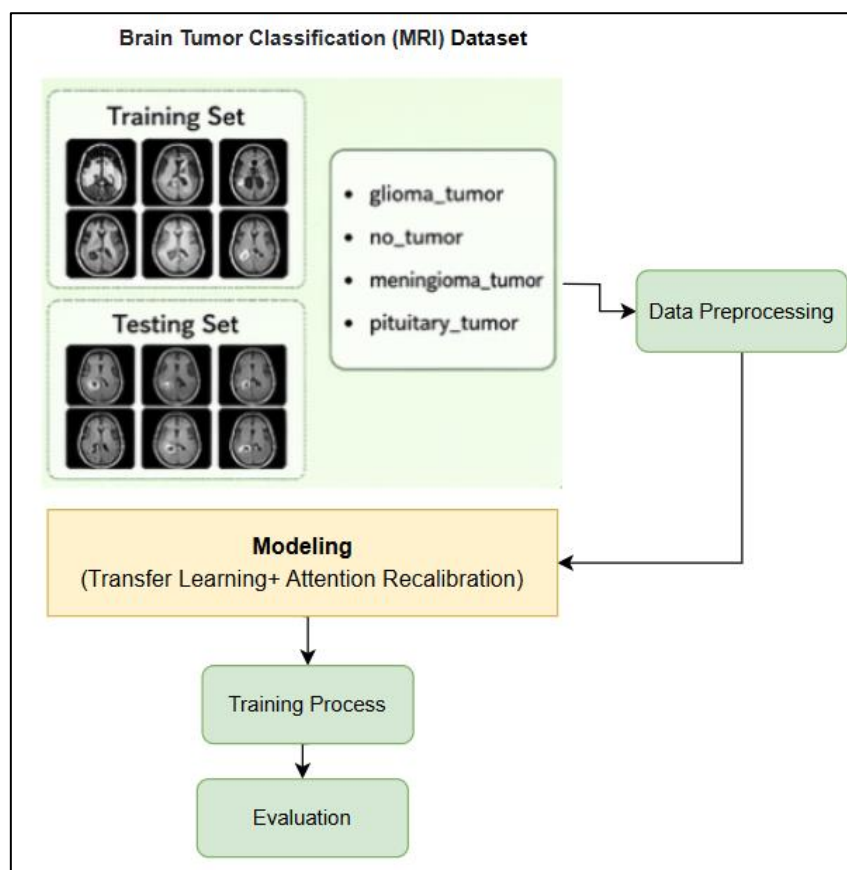


Figure 1: Methodology steps for brain tumor classification on MRI images.

3.1 Brain Tumor Classification (MRI) Dataset

The dataset used in this work is publicly available on the Kaggle repository (Sartaj, 2025). The dataset, titled Brain Tumor Classification (MRI), consists of healthy and tumor-containing brain MRIs classified into four categories. The dataset consists of 3,264 MRIs in JPG format, 2,870 of which are in the training set and 394 in the testing set. During preprocessing, all images were resized to 150×150 pixels and represented as three-channel RGB images to ensure consistency with the input requirements of the deep learning model. Table 2 summarizes the class-wise distribution of the dataset used in this study.

Table 2: Distribution of MRI images in Brain Tumor Classification (MRI) Dataset.

Class Label	Training Set	Testing Set
Glioma	826	100
Meningioma	822	115
No Tumor	395	105
Pituitary	827	74
Total	2870	394

3.2 Data Preprocessing

The MRI scan images are grabbed from specific folders named after the classes and then loaded by using various image processing libraries. These steps are taken so that every image is rightly connected to its label. To have uniformity and be suitable as input to deep learning models, all pictures are made of the same size – 150×150 pixels. The pixel values are then transformed into numerical arrays which give us the features, whereas the labels are kept separately for a supervised learning setting. After that, the dataset is mixed randomly to get rid of the bias in order, and the training is able to generalize better the new data. At the end, the data is divided into training and testing parts, and the class labels are changed into one-hot vectors to enable multi-class classification.

3.3 Modeling

A system of brain tumor classification using transfer learning and attention-based feature refinement is proposed. As the core feature extractor, EfficientNetB0, which is pretrained on ImageNet, is used. Attention Recalibration Block is proposed with the Squeeze-and-Excitation (SE) mechanism, to enrich the channel representation of features. Then, the features are combined and passed through fully connected classification layers. The network architecture is described in detail in Table 3.

Table 3: Detailed architecture of the proposed EfficientNetB0 with attention recalibration network.

Stage	Layer/Operation	Output Shape	Configuration	Activation
Input	MRI Image	$150 \times 150 \times 3$	RGB Input Image	–
Feature Extraction	EfficientNetB0 Backbone (Frozen)	$5 \times 5 \times 1280$	ImageNet Pretrained	Swish
Attention Recalibration	Global Average Pooling	1280	Channel Descriptor Generation	–
Attention Recalibration	Dense Layer	80	Reduction Ratio = 16 (1280/16)	ReLU
Attention Recalibration	Dense Layer	1280	Channel Expansion	Sigmoid
Attention Recalibration	Channel-wise Multiplication	$5 \times 5 \times 1280$	Feature Recalibration	–
Feature Aggregation	Global Average Pooling	1280	Feature Vector Generation	–
Classification Head	Dense Layer	128	Fully Connected Layer	ReLU
Regularization	Dropout	128	Dropout Rate = 0.5	–
Output Layer	Dense Layer	4	Four Tumor Classes	Softmax

- Total Parameters: 4,418,855
- Trainable Parameters: 369,284
- Non-Trainable Parameters: 4,049,571

The differences in architecture between a standard CNN classification system and the proposed attention-based EfficientNetB0 system are displayed in Figure 2. Feature extraction and classification in standard systems is a two-step process. In contrast, the system proposed here utilizes an attention recalibration block to further focus on the most critical feature channels prior to classification.

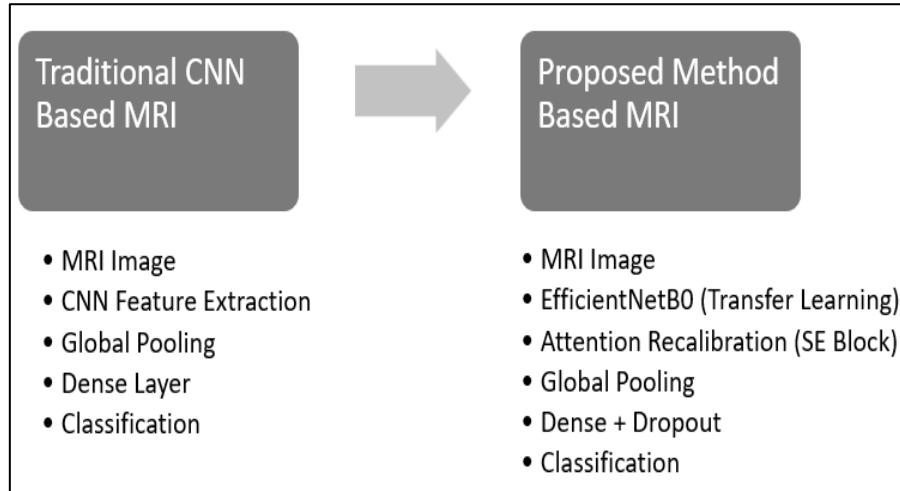


Figure 2: Traditional CNN vs proposed framework for brain tumor classification using MRI images.

The pretrained base model is brought in from an EfficientNet-based backbone, becoming the main feature extractor. It is this backbone that implements Mobile Inverted Bottleneck (MBConv) blocks with depthwise separable convolutions, aiming to capture spatial and semantic features effectively and at the same time, lowering the computational cost. The pretrained weights enable the model to refer to its prior knowledge, thereby speeding up convergence and also enhancing generalization capability, which is highly beneficial in case of scarce datasets.

In addition to the main feature extraction pathway, an Attention Recalibration Block is used. This block follows the SE mechanism, where global average pooling first summarizes channel-wise information into a compact descriptor. The descriptor is passed through two fully connected layers to learn channel dependencies. The layers contain 80 neurons with ReLU activation and 1280 neurons with Sigmoid activation. The attention weights are then multiplied with the original feature to the proposed systems focus. This helps the system focus on channels that contain the most relevant information, in this case, features related to brain tumor classification.

The Attention Recalibration Block is implemented using the SE mechanism to adaptively emphasize informative feature channels. First,

global average pooling is applied to each channel of the input feature map to generate a compact channel descriptor:

$$z(c) = (1/(H \times W)) \times \sum_{i=1}^{H} \sum_{j=1}^{W} X_c(i, j) \quad Eq. (1)$$

where H and W denote the height and width of the feature map, respectively, and X_c represents the c-th channel. The extracted channel descriptors are then passed through two fully connected layers to learn channel-wise dependencies:

$$s = Sigmoid(W2 \times ReLU(W1 \times z)) \quad Eq. (2)$$

where W1 and W2 are trainable weight matrices. Finally, the learned channel weights are multiplied with the original feature maps to obtain the recalibrated representation:

$$X\hat{c} = sc \times X_c \quad Eq. (3)$$

where sc denotes the learned importance weight for channel c . This attention mechanism enhances discriminative features while suppressing less relevant information, thereby improving classification performance. Then, the design has a feature aggregation layer, a layer where high-dimensional feature maps are downscaled into a tiny representation by means of global average pooling. This operation changes the 3D feature maps into a one-dimensional feature vector, keeping the main information whilst drastically lowering the dimensionality. This phase serves as a link between convolutional feature extraction and fully connected classification.

The classification head consists of a fully connected Dense layer containing 128 neurons with ReLU activation, followed by a Dropout layer with a rate of 0.5 to reduce overfitting. Finally, a Dense output layer containing four neurons corresponding to the four tumor categories employs the Softmax activation function to generate probability distributions across all classes. This configuration enables effective multi-class brain tumor classification while maintaining model generalization capability.

3.4 Training Process

The training setup was done through multiple callbacks that the developers utilized to improve generalization, and at the same time, keep overfitting at bay. The EfficientNetB0 backbone was frozen during the training of the attention-enhanced classifier. The model whose performance was the best on the validation set was saved, while EarlyStopping checked the validation loss and terminated the training if no progress was made for a certain period of time. On top of that, the learning rate was changed automatically to keep convergence stable, especially when the validation performance was steady.

3.5 Evaluation

A confusion matrix was used to classify the model's performance, and describes the predicted label by the model and the actual label for each of the four tumor categories. The performance of the proposed model was evaluated:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad Eq. (4)$$

$$Precision = TP / (TP + FP) \quad Eq. (5)$$

$$Recall = TP / (TP + FN) \quad Eq. (6)$$

$$F1 - Score = (2 \times Precision \times Recall) / (Precision + Recall) \quad Eq. (7)$$

where TP represents True Positives, TN represents True Negatives, FP represents False Positives, and FN represents False Negatives. Since brain tumor classification is a multi-class problem, weighted averaging was employed to compute Precision, Recall, and F1-Score across all classes, providing an overall assessment of model performance.

Results

Training results suggest convergence was stable through the whole training, while accuracy which was high from training early epochs was still maintained well. Figure 3 shows the loss curves with very small fluctuations indicating that the model has effectively learned without the problem of overfitting. Likewise, Figure 4 shows the accuracy graph with consistently high accuracy for both training and validation, which confirms that the model is reliable and has the ability to generalize well.

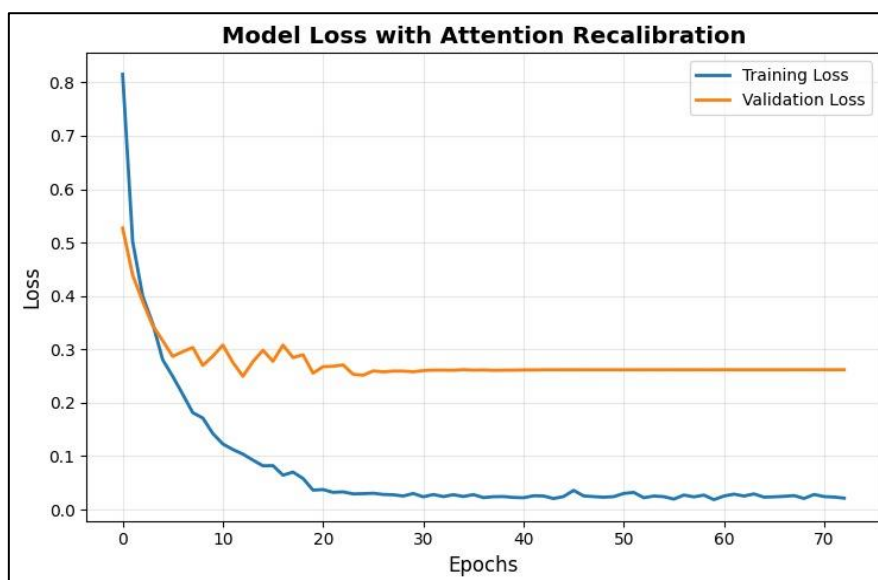


Figure 3: Training and validation loss across 70 epochs.

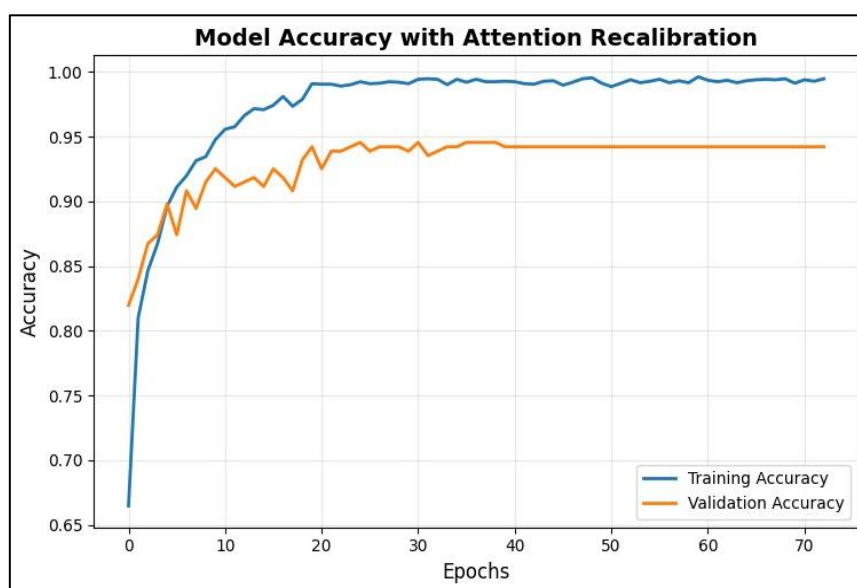


Figure 4: Training and validation accuracy across 70 epochs.

Results of the validation shown in Figure 5 demonstrate that the attention-upgraded model gained its highest performance at epoch 20, reaching a validation accuracy of 97.05% together with a validation loss of 0.0959. These results prove the power of the attention adaptation process combined with the pretrained backbone for enhancing discriminative learning. The consistency of the measures is an additional sign that the model is not overfitting but rather keeping an excellent level of prediction ability.

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ATTENTION-ENHANCED MODEL - BEST RESULTS:
Validation Accuracy: 0.9705 (97.05%)
Validation Loss: 0.0959
Best at epoch: 20
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Figure 5: Validation performance of the attention-enhanced model.

To further assess classification performance, the trained model was evaluated on the test set using weighted Precision, Recall, and F1-Score metrics. The overall results are summarized in Table 4.

Table 4: Overall performance metrics of the proposed attention-enhanced EfficientNetB0 model on the test set.

Metric	Value
Precision (Weighted)	93.35%
Recall (Weighted)	93.27%
F1-Score (Weighted)	93.24%

The confusion matrix for the proposed model on the test dataset is found in Figure 6. The results show that the model has strong classification performance, as MRI images from the test dataset were successfully classified in the four categories. The confusion matrix and the results of Table 4 show that the proposed attention-enhanced EfficientNetB0 model is valid.

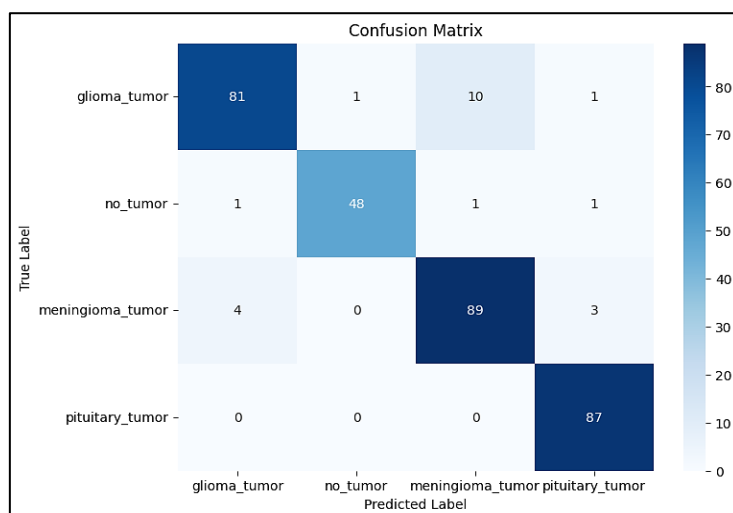


Figure 6: Confusion Matrix of the proposed attention-enhanced EfficientNetB0 model on the test set.

A detailed comparison of the proposed attention-based EfficientNet model with other techniques, including MobDenseNet by Afroj et al. (2025), as well as baseline architectures like MobileNetV1 DenseNet121 Xception InceptionV3 VGG19, and ResNet101V2, reveals the superiority of the proposed method when using the same dataset. Although MobDenseNet showed excellent performance by combining features from different levels, the new model uses EfficientNetB0 plus SE attention to get even higher accuracy (97.05%) and at the same time lower complexity. On the one hand, traditional CNNs are less precise and more expensive to run. On the other hand, the proposed approach is not only more effective but also uses fewer resources. Additionally, the attention mechanism improves features discrimination in a simpler way, i. e. without multi-architecture fusion, so that the model can be easily and efficiently expanded. Table 5 contains a summary of this discussion where it is clearly shown that the new model achieves the highest accuracy among all the models that have been compared.

Table 5: Comparative performance of the proposed model and existing CNN architectures on Brain Tumor Classification (MRI) Dataset.

Model	Accuracy
MobileNetV1	93.8%
Xception	88.9%
DenseNet121	91.7%
InceptionV3	91.8%
MobDenseNet	96.02%
(Afroj <i>et al.</i> , 2025)	
Proposed Model	97.05%

Conclusion

This study describes the creation of an advanced deep learning model which leverages attention for the automated classification of brain tumors using MRI data. The model is built on transfer learning with a pretrained EfficientNetB0 and employs an attention recalibration mechanism using the Squeeze-and-Excitation (SE) Block. The use of the SE Block is intended to be beneficial for both feature construction and the classification task. The results show the model is effective, as a frozen pretrained backbone led to a validation accuracy of 97.05% and the integration of the attention mechanism helped the network improve the classification of almost all four tumor types, as well as focus on the relevant features of the tumor.

With that said, the study has its limitations. The model was only assessed on one publicly available MRI dataset, so its use on other datasets with different protocols, different scanners, or even different imaging centers is not guaranteed. Additionally, keeping the EfficientNetB0 backbone frozen during training was intended to be computationally beneficial, however, that may have been a detriment to the model learning task-relevant features. The study also did not propose the use of other imaging or clinical data, or other modalities, that may improve the classification. In general, the study adds to the current state of research on attention-based transfer learning models applied to multi-class classification of brain tumors and their usefulness in the field of medical image analysis.

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التعلم بالنقل المحسن مع إعادة معايرة الانتباه لتصنيف أورام الدماغ باستخدام صور الرنين

المغناطيسي (MRI)

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مستخلص البحث:

لا يزال التعرف الدقيق والسريع على أورام الدماغ في صور التصوير بالرنين المغناطيسي مهمة معقدة بسبب تنوع خصائص الأورام والقيود المرتبطة بالطرق اليدوية، مما أدى إلى تطوير أنظمة ذكية مؤتمتة. يقترح هذا العمل نموذج تعلم عميق معزز بالانتباه يجمع بين التعلم الانتقالي باستخدام النموذج المُدرَّب مسبقاً EfficientNetB0 وآلية الانتباه من نوع Squeeze-and-Excitation (SE) لتحسين تمثيل الخصائص. تتكون مجموعة بيانات التدريب من 3264 صورة رنين مغناطيسي للدماغ موزعة على أربع فئات: الورم الدبقي (Glioma)، الورم السحائي (Meningioma)، ورم الغدة النخامية (Pituitary tumor)، وعدم وجود ورم. تشمل خطوات المعالجة المسبقة للصور تغيير الحجم، والتطبيع، وترميز التسميات. تجمع البنية المقترحة بين استخلاص خصائص فعال، وإعادة معايرة قائمة على الانتباه، ورأس تصنيف مُنظَّم لتحقيق نتائج أفضل. كما تم اعتماد استراتيجية منهجية لتطوير النموذج باستخدام الإيقاف المبكر وضبط معدل التعلم التكيفي لضمان تقارب موثوق. تُظهر النتائج أن الإطار المقترح يحقق دقة تحقق بلغت 97.05% وخسارة تحقق مقدارها 0.0959 عند أفضل حقبة تدريب. بالإضافة إلى ذلك، يتفوق النموذج على النماذج التقليدية مثل MobileNetV1 وDenseNet121 وكذلك النماذج الهجينة الحديثة. علاوة على ذلك، تُبين هذه الدراسة أن استخدام آليات الانتباه يُحسن أداء التصنيف بشكل ملحوظ مع الحفاظ على انخفاض التكلفة الحسابية.

الكلمات المفتاحية: تصنيف أورام الدماغ، التصوير بالرنين المغناطيسي، التعلم العميق، التعلم الانتقالي، آلية الانتباه، EfficientNetB0.

ملاحظة: هل البحث مستل من رسالة ماجستير او اطروحة دكتوراه؟ كلا