Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 2, April 2026
DOI : https://doi.org/10.33395/sinkron.v10i2.15931
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Improving Brain Tumor Classification Performance Using EfficientNetB0 Integrated with CBAM Attention Mechanism

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Submitted :Feb 21, 2026 | **Accepted** : March 1, 2026 | **Published** : April 2, 2026

Abstract: Accurate classification of brain tumors using magnetic resonance imaging (MRI) requires robust automated methods to support clinical diagnosis, particularly when tumor types exhibit subtle visual differences. This study integrates the Convolutional Block Attention Module (CBAM) into the EfficientNetB0 architecture to enhance feature representation for multi-class brain tumor classification. The dataset consists of 6,056 MRI images categorized into three classes: Brain Glioma (2,004 images), Brain Meningioma (2,004 images), and Brain Tumor (2,048 images). The data are divided into training, validation, and independent test sets under identical experimental conditions for both models to ensure fair evaluation. EfficientNetB0 with CBAM achieves a training accuracy of 99.76% and a validation accuracy of 99.45%, with corresponding losses of 0.0085 and 0.0241. On the independent test set, the proposed model attains 99.25% accuracy with a loss of 0.0207. In contrast, the baseline EfficientNetB0 records training, validation, and test accuracies of 52.68%, 46.20%, and 43.32%, respectively, with substantially higher loss values. The performance gap is associated with the baseline model's limited ability to emphasize discriminative tumor regions, whereas CBAM refines both channel and spatial features. The proposed model achieves macro-average precision, recall, and F1-score of 0.99, compared to approximately 0.54 precision and recall and 0.50 F1-score for the baseline. Although computational time per evaluation step increases from 395 ms to 601 ms, the accuracy improvement remains substantial. These findings demonstrate that lightweight attention integration significantly enhances classification reliability, supporting more accurate computer-aided brain tumor diagnosis.

Keywords: Brain Tumor Classification; Magnetic Resonance Imaging (MRI); EfficientNetB0; CBAM; Deep Learning

INTRODUCTION

Brain tumors are among the most critical neurological disorders, necessitating accurate and timely diagnosis to enhance patient prognosis and inform treatment planning. Magnetic Resonance Imaging (MRI) is the primary imaging modality for detecting and characterizing brain tumors, as it provides high soft-tissue contrast without exposing patients to ionizing radiation. Manual interpretation of MRI scans relies heavily on radiological expertise and is subject to inter-observer variability. These limitations have prompted the development of automated computer-aided diagnostic systems to support clinical decision-making. Recent advances in deep learning have transformed medical image analysis, particularly through the application of convolutional neural networks (CNNs). CNN-based models effectively extract hierarchical features directly from imaging data, eliminating the need for handcrafted feature engineering. Architectures such as EfficientNet employ compound scaling strategies that balance network depth, width, and resolution, resulting in improved performance and optimized computational

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efficiency (Tan & Le, 2019). EfficientNet-based methods have gained significant attention in medical imaging tasks due to their ability to maintain high accuracy while reducing parameter complexity.

Recent research on brain tumor classification demonstrates that deep learning frameworks yield promising results. Specifically, convolutional neural network (CNN) methods achieve high accuracy in distinguishing brain_glioma, brain_meningioma, and brain_pituitary tumors using MRI datasets (Cheng et al., 2015; Díaz-Pernas et al., 2021). More recent research explores transfer learning strategies and fine-tuning of pre-trained networks to enhance classification performance on limited medical dataset (Aamir et al., 2022; Rehman et al., 2020). Despite these advancements, distinguishing tumor subtypes remains challenging because of overlapping visual characteristics and intra-class variability.

To address these limitations, attention mechanisms gain increasing interest in medical image classification. Attention modules enable neural networks to focus on the most informative spatial regions and feature channels, thereby improving discriminative representation. The Convolutional Block Attention Module (CBAM) introduces a lightweight yet effective combination of channel and spatial attention that can be integrated into existing CNN architectures (Woo et al., 2018). In medical imaging applications, attention-based models demonstrate improved interpretability and classification robustness (Ke et al., 2026; Rasheed et al., 2024). More recent studies in healthcare imaging confirm that attention-enhanced networks improve diagnostic accuracy, particularly in tasks involving subtle anatomical differences (Guo et al., 2016; Saraei & Liu, 2023).

However, existing studies often evaluate models under different experimental settings, making fair comparison difficult. Furthermore, limited attention has been given to systematically analyzing how lightweight attention modules influence EfficientNet-based architectures in multi-class MRI classification settings. This gap leaves uncertainty regarding the actual contribution of attention-based feature recalibration in compound-scaled networks. Although several works explore deep CNNs for brain tumor detection, limited studies specifically investigate the integration of CBAM within EfficientNet architectures for multi-class tumor classification. The combination of EfficientNet's compound scaling and CBAM's feature refinement mechanism offers potential advantages in capturing discriminative tumor features while maintaining computational efficiency. Therefore, this study proposes an EfficientNetB0 model integrated with CBAM to improve multi-class brain tumor classification performance using MRI images. The main contributions of this study are summarized as follows: (1) The integration of the Convolutional Block Attention Module (CBAM) into the EfficientNetB0 architecture for multi-class brain tumor classification; (2) A controlled comparative evaluation between baseline EfficientNetB0 and EfficientNetB0 + CBAM under identical training, validation, and testing conditions. The evaluation includes training and validation performance, independent test set analysis, and detailed classification metrics such as precision, recall, F1-score, and confusion matrix distribution. By presenting both quantitative and class-level evaluation, this study aims to provide empirical evidence regarding the effectiveness of attention-based feature enhancement in medical image classification tasks.

LITERATURE REVIEW

Deep Learning in Brain Tumor Classification

The use of deep learning in medical image analysis is rapidly expanding, particularly for brain tumor classification using magnetic resonance imaging (MRI). Convolutional neural networks (CNNs) offer a robust framework for extracting hierarchical and discriminative features directly from imaging data. In contrast to traditional machine learning methods that depend on handcrafted features, CNN-based techniques facilitate automatic feature learning and frequently achieve superior performance in complex classification tasks. In recent years, deep learning methods, especially CNNs, have become increasingly prominent in medical image analysis. Within brain tumor imaging, CNN-based models are extensively utilized for classification, segmentation, and detection tasks (Ke et al., 2026; Krizhevsky et al., 2012; LeCun et al., 2015; Sadr et al., 2025; Wong et al., 2025). A primary strength of convolutional neural networks (CNNs) is their capacity to automatically learn hierarchical feature representations from raw image data. This enables CNN models to identify complex spatial patterns more effectively than traditional machine learning approaches that rely on handcrafted feature extraction (Lu et al., 2025).

EfficientNet and Model Scaling Strategies

EfficientNet employs a compound scaling method that simultaneously balances network depth, width, and input resolution to enhance both performance and computational efficiency (Tan & Le, 2019). Instead of arbitrarily increasing model dimensions, EfficientNet applies a principled scaling strategy that achieves improved accuracy with fewer parameters compared to conventional architectures. In medical imaging applications, EfficientNet demonstrates strong performance across various classification tasks. For example, studies applying EfficientNet variants to medical image datasets report improved diagnostic accuracy (Shah et al., 2022; Shashidhar et al., 2024). The ability of EfficientNet to capture complex visual features with optimized scaling makes it particularly suitable for MRI-based classification tasks where image resolution and feature granularity play important roles. Recent

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investigations further confirm that EfficientNet-based transfer learning strategies enhance generalization in limited medical datasets (Kshatri & Singh, 2023; Mienye et al., 2025).

Attention Mechanisms in Medical Image Analysis

Attention mechanisms have become increasingly prominent in deep learning research because they enable models to focus on informative regions and feature channels. The Convolutional Block Attention Module (CBAM) presents a lightweight attention framework that sequentially applies channel and spatial attention to enhance intermediate feature maps (Woo et al., 2018). The channel attention mechanism adaptively recalibrates feature responses by modelling relationships among channels, whereas the spatial attention mechanism highlights important spatial regions within feature maps. This sequential refinement enhances the representational capacity of convolutional layers without introducing substantial computational overhead. Because of its simplicity and modular design, CBAM can be seamlessly embedded into existing CNN backbones, making it attractive for medical imaging applications where computational efficiency and scalability remain relevant considerations.

By recalibrating feature responses, CBAM enhances representational power without significantly increasing computational burden. More recent systematic reviews confirm that attention modules contribute positively to performance in various medical imaging domains, including tumor detection and organ segmentation (Saraei & Liu, 2023). Specifically for brain tumor classification, attention-enhanced CNNs show improved sensitivity and class discrimination when compared to conventional CNN models (Abd-Ellah et al., 2019).

METHOD

This section introduces a deep learning framework for brain tumor classification that employs EfficientNetB0 in combination with the Convolutional Block Attention Module (CBAM). The main contribution of this study is the improved feature representation of EfficientNetB0 achieved through channel and spatial attention mechanisms, which allow the model to concentrate on tumor-relevant regions in MRI images and reduce the influence of irrelevant background information.

Dataset Description

The Brain Cancer MRI dataset developed by Rahman (Rahman, 2024) was employed in this study. This dataset comprises 6,056 labeled brain MRI images prepared for tumor classification research. The dataset comprises images categorized as Brain Glioma (2,004 images), Brain Meningioma (2,004 images), and Brain Tumor (2,048 images). These images were collected from multiple hospitals in Bangladesh and annotated by medical experts to ensure annotation accuracy and case diversity. All images were standardized to a resolution of 512 × 512 pixels to maintain consistent preprocessing and ensure compatibility with the input requirements of deep learning models. Representative samples from the dataset are presented in Figure 1.

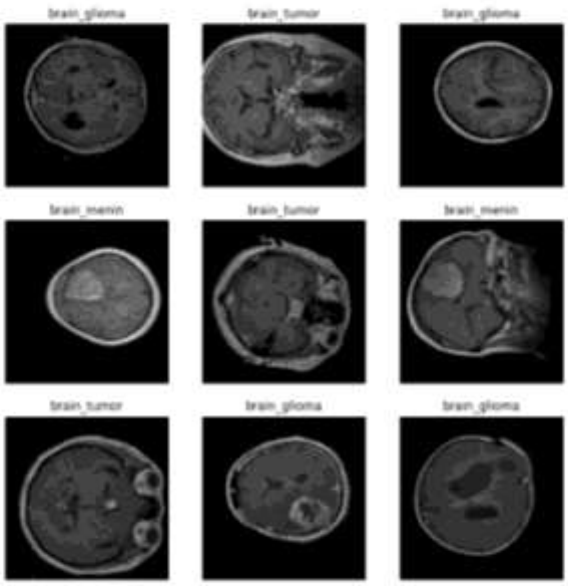

Fig. 1 Brain Cancer MRI Dataset

For experimental purposes, The dataset was randomly divided into three subsets using a stratified sampling approach to preserve proportional class distribution. Specifically, 70% of the data was allocated for training, 15% for validation, and 15% for testing. The training set was used for model parameter learning, the validation set for

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e-ISSN : 2541-2019
p-ISSN : 2541-044X

monitoring performance and tuning hyperparameters, and the testing set for providing an unbiased evaluation of final model performance.

Data Preprocessing

MRI images were resized to 224 × 224 pixels with three channels to satisfy the input specifications of the convolutional neural network architecture. Pixel intensity values were normalized to a range of 0 to 1 by dividing each value by 255. This normalization contributed to greater stability during the optimization process. Preprocessing and data loading were performed using an automatic data generator. Of the total training data, 15% was reserved as validation data to ensure a consistent separation between training and validation subsets. Data augmentation was applied only to the training data to enhance the model's generalization. The validation data remained unaugmented to ensure an objective evaluation of model performance.

The augmentation techniques implemented in this study consisted of random rotation up to 15 degrees, zoom adjustment up to 10%, and horizontal flipping. These methods were selected to simulate natural variations in MRI image appearance while preserving essential anatomical structures. Additionally, the data generator managed batch processing and categorical label encoding to support efficient multi-class classification during training.

Model Architecture Design (EfficientNetB0 + CBAM)

The proposed model employs EfficientNetB0 as the primary backbone network for feature extraction. EfficientNetB0 is selected due to its compound scaling strategy, which systematically balances network depth, width, and input resolution. This architecture facilitates robust feature representation while preserving computational efficiency. In this study, the backbone is initialized with pretrained weights from the ImageNet dataset as part of a transfer learning methodology. The original fully connected classification layer of EfficientNetB0 is removed, retaining only the convolutional base to generate high-level feature maps from brain MRI inputs. During the initial training phase, the backbone parameters are kept frozen. This approach preserves the pretrained visual representations and allows the newly added layers to adapt specifically to tumor characteristics in MRI images.

To enhance feature discrimination, a Convolutional Block Attention Module (CBAM) is incorporated following the backbone output. In medical image analysis, not all extracted features contribute equally to diagnostic accuracy. Specific channels and spatial regions may contain more relevant tumor information, whereas others primarily represent background structures. Consequently, CBAM is employed to refine the extracted features through sequential channel and spatial attention mechanisms.

Let the output feature tensor from EfficientNetB0 be defined as:

$$F \in \mathbb{R}^{H \times W \times C}$$

where H and W denote the spatial dimensions, and C represents the number of channels. First, global average pooling and global max pooling operations are applied across the spatial dimensions to obtain compact channel descriptors. For average pooling:

$$z_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} F_{i,j,c}$$

This operation produces a channel descriptor vector:

$$z \in \mathbb{R}^{C}$$

The descriptor is then passed through two fully connected layers with shared weights:

$$M_c(F) = \sigma(W_2 \cdot \delta(W_1 \cdot z))$$

where δ denotes the ReLU activation function, σ represents the sigmoid function, and W_1 and W_2 are learnable parameters. The resulting channel attention map:

$$M_c(F) \in R^{C}$$

contains normalized weights between 0 and 1. These weights are applied to the original feature tensor through element-wise multiplication:

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$$F' = M_c(F) \otimes F$$

this operation emphasizes informative channels while reducing less relevant responses.
After channel refinement, spatial attention is applied to determine which spatial locations contain more relevant tumor information. Initially, average pooling and max pooling are applied along the channel dimension. The resulting feature maps are then concatenated and processed through a convolutional layer:

$$M_s(F') = \sigma(f^{7\times7}([AvgPool(F');\ MaxPool(F')]))$$

where $f^{7\times7}$ denotes a convolution operation with a 7×7 kernel. The spatial attention map is then applied to the refined feature tensor:

$$F'' = M_s(F') \otimes F'$$

The final refined feature representation:

$$F'' \in R^{H \times W \times C}$$

is forwarded to the classification head, which consists of Global Average Pooling, fully connected layers, dropout regularization, and a Softmax activation function for multi-class prediction.

The integration of EfficientNetB0 with CBAM enables the network to not only extract hierarchical features efficiently but also selectively emphasize diagnostically relevant channels and spatial regions. This combination strengthens tumor-related representations while maintaining computational efficiency, making the architecture suitable for brain MRI classification tasks. Following attention refinement, the enhanced feature maps are forwarded to the classification head to generate the final prediction. This stage transforms spatial feature representations into a compact discriminative vector and maps it to tumor class probabilities. Global average pooling is applied across spatial dimensions to summarize each channel into a single representative value, producing a feature vector:

$$v_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} F'_{i,j,c}\ , v \in \mathbb{R}$$

This vector is passed through a fully connected layer with rectified linear activation to learn nonlinear class discriminative combinations of the extracted features:

$$h = \delta(W_f \cdot v + b_f)$$

where W_f and b_f are trainable parameters and δ denotes the ReLU activation function. To improve generalization and reduce overfitting risk, dropout regularization is applied to the hidden representation during training. The final prediction layer consists of a dense layer with three output neurons, each representing a tumor category. The Softmax activation function converts the output logits into normalized class probabilities:

$$p_k = \frac{e^{zk}}{\sum_{j=1}^{3} e^{zj}}$$

where p_k denotes the predicted probability for class k. The resulting probability distribution is used to determine the final class label for each MRI image.

Training Configuration

The training procedure employs transfer learning by initializing the EfficientNetB0 backbone with pretrained ImageNet weights. This initialization facilitates robust feature extraction and expedites model convergence. In the initial phase, the backbone layers are kept frozen, enabling the CBAM attention module and classification layers to adapt specifically to tumor-related features in MRI images.

The optimization process utilizes the Adam optimizer with an initial learning rate of 1×10^{-4}. Categorical cross-entropy is employed as the loss function for multi-class classification, while accuracy serves as the primary evaluation metric during training. A batch size of 32 is chosen to balance computational efficiency and gradient stability, and the maximum number of training epochs is set to 20. To promote generalization, validation loss is

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monitored throughout training. Early stopping is implemented to terminate training if no improvement in validation loss is observed for five consecutive epochs, with automatic restoration of the best-performing weights. Additionally, the learning rate is reduced by a factor of 0.3 if the validation loss remains unchanged for three epochs, facilitating finer optimization near convergence. Table 1 provides a summary of the training hyperparameters.

Table 1
Training Hyperparameter Configuration

Component	Configuration
Backbone Network	EfficientNetB0
Pretrained Weights	ImageNet
Attention Module	CBAM (Channel + Spatial Attention)
Optimizer	Adam
Initial Learning Rate	0.0001 (1×10^{-4})
Loss Function	Categorical Cross-Entropy
Batch Size	32
Maximum Epochs	20
Early Stopping Patience	5 epochs
Learning Rate Reduction	Factor 0.3 (patience 3 epochs)
Evaluation Metric	Accuracy

The configuration in Table 1 reflects a balanced training strategy that combines transfer learning, adaptive optimization, and regularization mechanisms. This setup supports stable convergence while reducing overfitting risk and computational cost, making it suitable for medical image classification tasks.

Performance Evaluation

Model performance is assessed using multiple quantitative metrics to provide a comprehensive evaluation of classification outcomes on brain MRI images. The primary indicators of overall performance are accuracy and loss. Accuracy quantifies the proportion of correctly classified samples relative to the total number of samples, whereas loss measures the optimization error generated during training. Accuracy is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP denotes True Positives, TN True Negatives, FP False Positives, and FN False Negatives. For a more comprehensive class-wise evaluation, precision, recall, and F1-score are calculated. Precision quantifies the proportion of correctly predicted positive instances among all instances predicted as positive:

$$Precision = \frac{TP}{TP + FP}$$

Recall indicates the ability of the model to correctly identify actual positive instances:

$$Recall = \frac{TP}{TP + FN}$$

The F1-score combines precision and recall into a single metric using the harmonic mean:

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The reported classification results include macro-average precision, recall, and F1-score in addition to overall accuracy. The macro-average metric is calculated by first determining the evaluation metric for each class independently, followed by computing the unweighted mean across all classes. This method assigns equal importance to each class, regardless of sample size. As a result, macro-average metrics offer a comprehensive assessment of model performance across all categories without bias from class distribution. In multi-class medical image classification tasks, such as in this study, macro-average evaluation ensures that performance is not disproportionately influenced by a single class with higher predictive accuracy.

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In addition to numerical metrics, a confusion matrix is employed to analyze the distribution of predictions across classes and to identify patterns of misclassification. This analysis facilitates the identification of tumor categories that are more challenging to distinguish. All evaluation metrics are computed on both validation and test sets to ensure that the reported results reflect the model's generalization capability rather than its performance on the training data.

RESULT

This section reports the experimental results from implementing the proposed EfficientNetB0 combined with CBAM model on the brain MRI dataset. Results encompass training performance, validation performance, and final evaluation on the test dataset. Findings are provided as numerical metrics, tables, and graphical representations, without interpretation or conclusion.

Training and Validation Performance

The training process was limited to a maximum of 20 epochs, incorporating early stopping and adaptive learning rate scheduling. Throughout training, accuracy and loss metrics were monitored for both the training and validation subsets. Figure 2 illustrates the comparative training and validation performance of the proposed EfficientNetB0 + CBAM model versus the baseline EfficientNetB0 model.

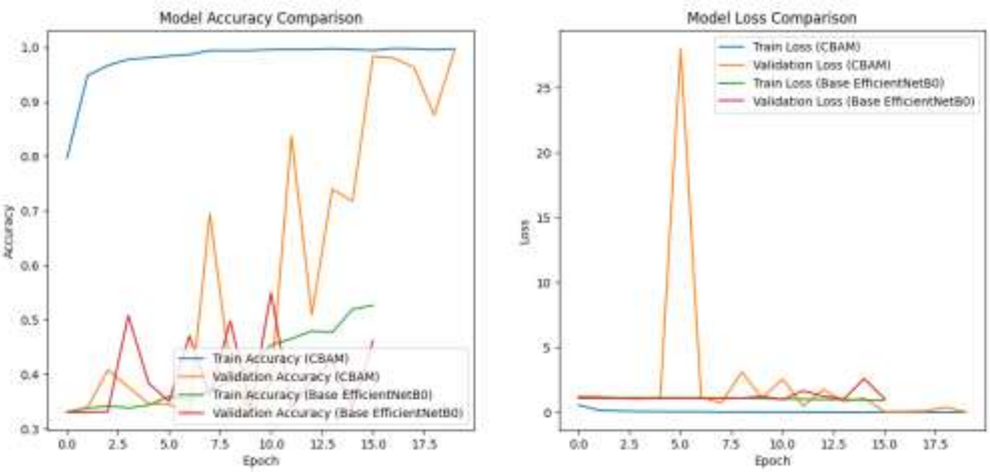

Fig. 2 Training and validation accuracy and loss curves for both models over epochs

Figure 2 illustrates that the EfficientNetB0 + CBAM model achieves a rapid increase in training accuracy during the initial epochs, rising from approximately 0.80 to above 0.99 within the first several epochs and remaining stable near 1.00 throughout training. The validation accuracy fluctuates in the early phase but increases substantially after the 10th epoch, reaching nearly 1.00 by the final epoch and indicating stable performance in later training stages. In comparison, the baseline EfficientNetB0 model shows a gradual improvement in training accuracy, increasing from approximately 0.33 at the outset to around 0.52 by the final epoch. Its validation accuracy fluctuates between 0.33 and 0.55 throughout training. The baseline model does not exhibit a strong convergence pattern within the same number of epochs as the proposed model.

Figure 2 also displays the training and validation loss curves for both models. The EfficientNetB0 + CBAM model demonstrates a sharp decrease in training loss, dropping from approximately 1.2 at the start to nearly zero by the final epoch. Although the validation loss fluctuates in the early epochs, including a notable spike around the sixth epoch, it decreases consistently after the mid-training phase and approaches zero in the final epochs. In contrast, the baseline EfficientNetB0 model exhibits a slower reduction in training loss, which remains above 0.9 at the end of training. Its validation loss fluctuates throughout training and does not show a substantial downward trend similar to the proposed model.

Table 2 summarizes the final training and validation performance for both models. The EfficientNetB0 + CBAM model achieves a final training accuracy of 0.9976 and a validation accuracy of 0.9945, with training and validation losses of 0.0085 and 0.0241, respectively. In contrast, the baseline EfficientNetB0 model attains a final training accuracy of 0.5268 and a validation accuracy of 0.4620, with corresponding training and validation losses of 0.9300 and 1.0331.

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Table 2
Final Training and Validation Performance

Model	Final Train Accuracy	Final Val Accuracy	Final Train Loss	Final Val Loss
EfficientNetB0	0.5268	0.4620	0.9300	1.0331
EfficientNetB0 + CBAM	**0.9976**	**0.9945**	**0.0085**	**0.0241**

The results shown in Figure 2 and Table 2 offer a comprehensive numerical and graphical summary of the training and validation processes for both models, based on the experimental setup detailed in the methodology section.

Test Set Evaluation

Performance results from the independent test dataset are reported for both the proposed EfficientNetB0 + CBAM model and the baseline EfficientNetB0 model. Evaluation utilized the best-performing weights from the training phase, with metrics including classification accuracy and categorical cross-entropy loss. The EfficientNetB0 + CBAM model completed evaluation in 29 steps, averaging approximately 601 ms per step. This model achieved a test accuracy of 0.9925 and a test loss of 0.0207. Validation metrics during this phase included a validation accuracy of 0.9923 and a validation loss of 0.0209. The close alignment between validation and test metrics demonstrates stable predictive performance on previously unseen data.

The baseline EfficientNetB0 model was similarly evaluated over 29 steps, with an average processing time of approximately 395 ms per step. This model achieved a test accuracy of 0.4332 and a test loss of 1.0780. Corresponding validation results included a validation accuracy of 0.5281 and a validation loss of 0.9798. These metrics differ markedly from those of the proposed model, particularly regarding predictive accuracy and loss magnitude. Table 3 summarizes the test set performance for both models, presenting the final numerical results from the evaluation procedure and reflecting the empirical outcomes of the experimental framework described in the methodology section. This section reports only quantitative findings, without interpretative conclusions.

Table 3
Test Set Performance Comparison

Model	Test Accuracy	Test Loss	Time per Step
EfficientNetB0	0.4332	1.0780	**395 ms**
EfficientNetB0 + CBAM	**0.9925**	**0.0207**	601 ms

Classification Metrics and Error Distribution Analysis

This section provides a comprehensive evaluation of classification performance using precision, recall, F1-score, and confusion matrix analysis for both models. The evaluation utilizes a test dataset comprising 907 images categorized into three classes: brain_glioma (300 samples), brain_menin (300 samples), and brain_tumor (307 samples). Quantitative results are reported based on the experimental findings. The confusion matrix for the EfficientNetB0 with Convolutional Block Attention Module (CBAM) model is shown in Figure 3. The matrix is defined as follows:

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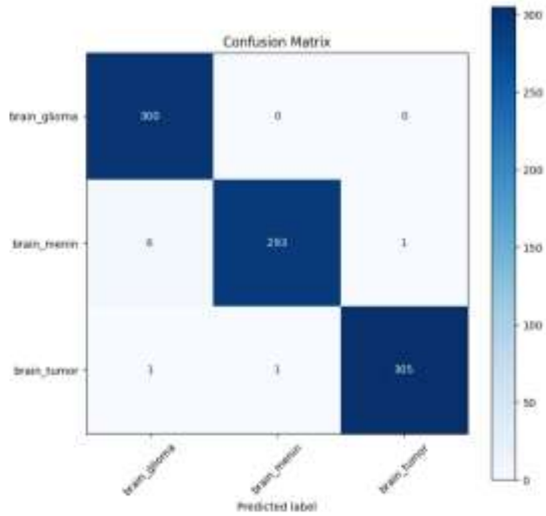

Fig. 3 The confusion matrix of the EfficientNetB0 + CBAM

According to the classification report, the brain_glioma class achieved a precision of 0.98, recall of 1.00, and F1-score of 0.99. All 300 samples in this class were correctly classified, as shown in Figure 3, with no misclassification into other categories. The brain_menin class attained a precision of 1.00, recall of 0.98, and F1-score of 0.99. Of the 300 samples, 293 were correctly classified, while 6 samples were predicted as brain_glioma and 1 sample as brain_tumor. The brain_tumor class demonstrated a precision of 1.00, recall of 0.99, and F1-score of 1.00. Out of 307 samples, 305 were correctly classified, with only two minor misclassifications distributed to the other classes. The overall accuracy of the model was 0.99. Macro-average precision, recall, and F1-score were all 0.99, indicating consistent performance across all classes. The error distribution presented in Figure 3 was minimal and did not reveal a dominant misclassification pattern.

Figure 4 illustrates the confusion matrix for the baseline EfficientNetB0 model, with the matrix defined as follows:

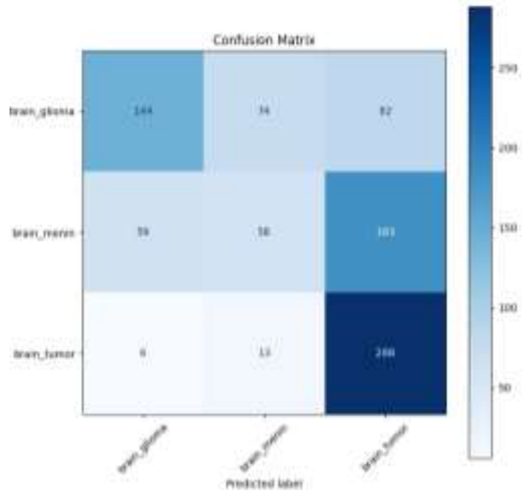

Fig. 4 The confusion matrix of the EfficientNetB0

According to the classification report, the brain_glioma class achieved a precision of 0.69, recall of 0.48, and an F1-score of 0.57. Figure 4 demonstrates that 144 out of 300 samples were correctly predicted, while 74 and 82 samples were misclassified into the other two categories, respectively. For the brain_menin class, the precision was 0.40, recall was 0.19, and the F1-score was 0.26. The confusion matrix reveals that only 58 of 300 samples were correctly classified, with 183 misclassified as brain_tumor and 59 as brain_glioma. The brain_tumor class achieved a precision of 0.52, recall of 0.94, and an F1-score of 0.67. Of 307 samples, 288 were correctly classified, while the remainder were incorrectly assigned to the other two classes.

The baseline model achieved an overall accuracy of 0.54, with macro-average precision and recall both at 0.54, and a macro-average F1-score of 0.50. The confusion matrix in Figure 4 indicates that misclassification is more prevalent between the brain_menin and brain_tumor classes. Table 4 provides a summary of the overall

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e-ISSN : 2541-2019
p-ISSN : 2541-044X

classification metrics for both models.

Table 4
Classification Performance Comparison

Model	Accuracy	Macro Precision	Macro Recall	Macro F1-Score
EfficientNetB0	0.54	0.54	0.54	0.50
EfficientNetB0 + CBAM	0.99	0.99	0.99	0.99

The results presented in this section describe the quantitative classification performance and error distribution patterns for both models, as illustrated in Figure 3 and Figure 4 and summarized in Table 4. These findings are reported as empirical outcomes derived from the experimental evaluation procedure.

DISCUSSIONS

This section discusses the experimental results from implementing EfficientNetB0 with and without the Convolutional Block Attention Module (CBAM). The analysis centers on performance differences, modeling implications, and the relevance of these findings to multi-class brain tumor classification. The model with CBAM demonstrates more stable convergence during training and validation compared to the baseline EfficientNetB0. Training curves show that the attention mechanism enables the network to achieve high accuracy in fewer epochs and maintain low validation loss in later training stages. In contrast, the baseline model exhibits limited improvement and less convergence stability. This comparison highlights the role of attention mechanisms in enhancing feature discrimination. Test set evaluations further reveal that the EfficientNetB0 + CBAM model achieves higher accuracy and lower loss than the baseline. These results indicate that channel and spatial attention improve the model's ability to focus on relevant tumor regions in MRI images. This capability is especially important in medical image classification, where different tumor types often share similar visual features.

The classification metrics reinforce these findings. The proposed model achieves balanced precision, recall, and F1-score across all classes, as demonstrated by macro-average values and confusion matrix analysis. Misclassification errors are minimal and not concentrated in any specific class. In contrast, the baseline model displays class-wise performance imbalance, with notably low recall for the brain_menin category and frequent misclassification as brain_tumor. This comparison suggests that the absence of an attention mechanism impairs the model's ability to distinguish between classes with subtle feature differences. Integrating CBAM increases computational time per evaluation step, but this cost is offset by significant gains in classification performance. In medical diagnostic applications, improved accuracy and reliability are typically prioritized over minor increases in processing time, particularly in critical decision-support systems.

In summary, these results address the challenge of improving multi-class brain tumor classification accuracy with deep learning architectures. The findings demonstrate that incorporating attention mechanisms into EfficientNet-based models yields measurable performance benefits. These outcomes further support the importance of attention-based feature refinement in enhancing representation learning for medical image analysis.

CONCLUSION

This study examines the implementation of EfficientNetB0 integrated with the Convolutional Block Attention Module (CBAM) for multi-class brain tumor classification using MRI images. The proposed model's performance is evaluated against the baseline EfficientNetB0 architecture under identical experimental conditions. Experimental results indicate that the CBAM-enhanced model achieves greater training stability, validation consistency, and test set accuracy. The inclusion of channel and spatial attention mechanisms enhances feature representation, resulting in higher precision, recall, and F1-score across all tumor classes. Confusion matrix analysis reveals a reduced rate of misclassification errors with the attention module. In contrast, the baseline EfficientNetB0 model exhibits limited convergence and lower classification performance, especially when differentiating between visually similar classes. While the proposed model incurs a modest increase in computational time per evaluation step, the gains in predictive accuracy and classification reliability constitute a significant advancement for medical image analysis.

These findings demonstrate that incorporating CBAM into EfficientNetB0 yields measurable benefits for multi-class brain tumor classification and highlights the importance of attention mechanisms in enhancing discriminative feature learning for medical imaging applications. The proposed framework therefore offers a practical and computationally feasible approach for supporting automated diagnostic systems. Nevertheless, this study has several limitations. The experiments are conducted on a single dataset without external or multi-center validation, which may limit the generalizability of the findings across diverse clinical settings and imaging protocols. In addition, only one attention mechanism (CBAM) is evaluated, and comparisons with other attention modules or transformer-based architectures are not explored. Future research may focus on validating the proposed model on larger and more heterogeneous datasets, including external clinical data. Further investigations could also compare alternative attention mechanisms, such as squeeze-and-excitation or self-attention modules, and explore hybrid CNN–transformer architectures to enhance global context modeling. Such extensions would provide deeper insight into the robustness, scalability, and clinical applicability of attention-enhanced deep learning models for brain tumor classification.

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