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Enhanced Brain Tumor Analysis: Integrating ResNet50 with Convolutional Block Attention Modules for Advanced Insights

Abstract: - The process of diagnosing brain tumors is a lengthy task that heavily relies on the experience of radiologists. However, deep learning techniques have become increasingly popular in automating the diagnosis of brain tumors, offering improved precision and effectiveness. One such technique, Convolutional Block Attention Modules (CBAM), uses attention-based models that dynamically enhance and refine diagnostic characteristics. However, the specific impact of using different attention methods, such as channel, spatial, or combined attention, within CBAM for brain tumor classification is yet to be fully explored.To address this gap, our research used ResNet50 coupled with CBAM to classify brain tumors. This novel approach demonstrated superior performance compared to existing methods, including Convolutional Neural Network. ResNet50-CBAM showed remarkable area under the curve (AUC), recall, precision, and accuracy of 99.53%, 99.11%, 98.75%, and 99.35%, respectively, using the same dataset.The fusion of ResNet-CBAM not only captures spatial context but also enhances feature representation, making it a promising integration into brain classification software platforms. This development could benefit doctors by improving brain tumor categorization and facilitating better clinical decision-making.

Keywords: Deep learning, ResNet50, Convolutional block attention, MRI, Brain tumor, Decision support.

I. INTRODUCTION

All physiological processes are controlled by the brain, which also serves as the command center of the central nervous system [1]. As a result, any anomalies in the brain can harm a person's health [2].A brain tumor is one such aberration that may be recognized by its enormous tissue volume. These tumors may be broadly categorized into two groups: benign tumors, which grow more slowly and are non-invasive, and malignant tumors, which multiply cells in brain tissue quickly and uncontrollably [3]. Brain tumors are divided into four categories by the World Health Organization (WHO), with Groups I and II being lower-grade tumors and levels III and IV being more dangerous [4]. Brain tumors are a dangerous medical disorder with a significant mortality rate [5]. For treatment to be successful, an early and precise diagnosis is also essential [6]. Following the use of MRI (magnetic resonance imaging) and CT (computed tomography) scans for diagnosis, pathological tests and a biopsy are carried out to confirm the diagnosis. Given that MRI is non-invasive and non-ionizing, it is advised as an imaging modality [7]. Research has shown that diagnosing medical pictures manually is difficult, time-consuming, and perhaps prone to errors [2], and that patient flow often makes these problems worse. The difficulty of detecting, categorizing, and rating tumors has been removed for neuro-oncologists due to the development of computer-aided diagnostic (CAD) techniques..

The growth of the principles of deep learning has been partly responsible for the notable advancements in computer-assisted health diagnosis [9]. Because of well-known examples like [1], deep machine learning has gained popularity for the diagnosis and categorization of brain tumors. One notable development in AI is deep transfer learning, which is now widely used in research on image classification, object identification, and visual categorization tasks [10]. Transfer learning, a kind of deep learning, has shown promise in the area of computer-aided diagnosis (CAD) of medical conditions. Recently, there has been emphasis on the use of pre-trained

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networks and transfer learning in neuro-oncology to extract features from brain MRIs [11].It has been shown that transfer learning works particularly well in scenarios with little datasets. Tariq and Naqvi, for instance, used efficientnetb4 to achieve 98.58% accuracy, whereas Ozkaraca et al. classified brain MRI images using DenseNet [2, 12]. In an analysis [13], AlexNet fared better than other CNN designs. Moreover, Shuffle-Net and support vector machine yielded the best results when Ali et al. used NasNet-Mobile, Shuffle-Net, and GoogLeNet topologies [14].

It has been shown that CNNs, or convolutional neural networks to capture both important and irrelevant data, despite being crucial in feature extraction for brain tumor prediction [15]. Because of this, there are currently few attention-based models for classifying brain tumors in the literature, and the ones that do exist mostly depend on CNNs and transfer learning [17]. Notably, by utilizing multi-channel data for supervised feature acquisition, a unique 3D-CNN architecture showed an accuracy of 89.9% [17]. The efficacy of utilizing full CNNs for precise tumor segmentation [18], incorporating correlation learning mechanisms for 96% accurate CT brain tumor detection [19], and utilizing different architectures like AlexNet, GoogLeNet, and ResNet50 for image classification [20] have all been demonstrated by other studies. ResNet50 performed the best among them, with an accuracy of 85.71%.

Motivated by the proven effectiveness of attention mechanisms in enhancing feature identification, this research aims to incorporate attention processes for the classification of brain tumors for enhanced functionality. Previous work by Shaikh et al. demonstrated enhanced biomedical image classification using the recurrent attention mechanism (RAM) [22], Liu [24] focused on the locations of mind skin in images to classify brain tumors by using the channel attention mechanism. To provide precedence to important features, we included the Convolutional Block Attention Module in this work [25]. The subsequent sections outline the structure of this paper. The second section describes the entire structure of the suggested classification technique and offers insights into the dataset used. After that, the experimental results obtained from our methods are presented in the third section. Our findings are concluded in the fourth section.

II. EXISTING WORK

Brain tumor classification using deep learning comprises autonomously classifying brain scan medical images into distinct tumor classifications using complex neural network designs. This approach uses deep learning models for accurate and fast classification detail to detect detailed patterns and features in raw image data.The ResNet50-CBAM fusion approach aims to enhance the level of discriminating between various brain classes, which should lead to better diagnostic outcomes. This combination attempts to improve the model's ability to reliably identify different brain states by extracting complex information from brain images and the contextual relationships between them. The processes include critical steps such as data collection, pre-processing, model selection, testing and deep learning model training. These are briefly outlined below.

A. Dataset and pre-processing methods

We used a publicly available dataset obtained from the paper of Nikbarwar [26]. This dataset contains a total of 7,023 brain MRI images classified into four groups: pituitary, meningioma, glioma, and no tumor. Table 1 presents an overview of the Brain Tumor MRI Dataset. Each image was resized to 256 by 256 pixels to ensure uniformity and compatibility as inputs to the model. In addition, a min-max normalization strategy was utilized to aid in accurate computation and reduce over fitting. The dynamic histogram equalization (DHE) approach was utilized to enhance the quality of the medical images.

Table 1.An overview of the Brain Tumor MRI Dataset

CLASS	TRAINING	TESTING
Glioma	1322	300
Meningioma	1339	307
No tumor	1596	404
Pituitary	1458	300

An image's contrast is a crucial factor in determining its quality [27]. Contrast enhancement is a method used to increase an image's visual quality, making it more appropriate for examination by machines as well as by humans. In order to improve contrast, we used Dynamic Histogram Equalization (DHE) [28], a method that corrects too bright or dark pictures. The classes in the dataset are shown in Figure 1 both before and after DHE were applied. After resizing, normalizing, and histogram equalization as pre-processing processes, the training set was used to build the model, and the testing sets were used to assess it.

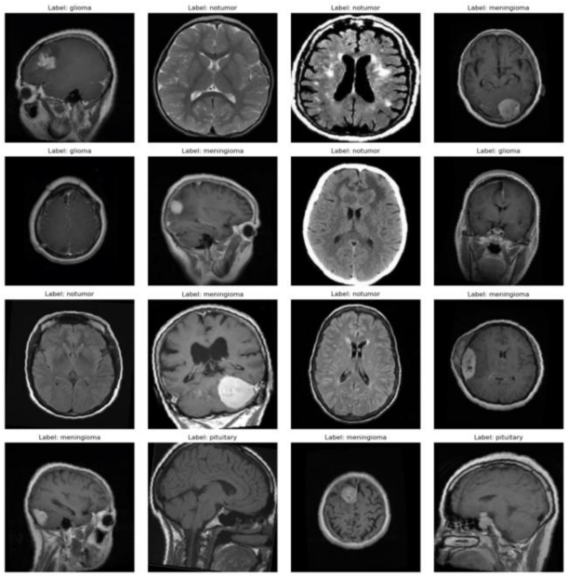

Figure 1. Load a batch of images and labels for visualization for the classes of the dataset before.

B. ResNet – 50 Network

The Residual Network (ResNet50) [29] was used in this investigation to extract features from preprocessed images using pre-trained Image Net weights [30]. The weights of the convolutional and max-pooling layers were locked to provide stability and prevent changes during this exercise. ResNet has been chosen over pre-trained networks due to its superior performance and ability to deal with the vanishing gradient problem [31].The features (F) recovered from ResNet50 were then transferred to the Convolutional Block Attention Module, as shown by the dashed lines in Figure 2. CBAM combines channel-based and spatial attention mechanisms [32, 33]. The channel attention technique emphasizes certain channels inside the feature map, enabling the model to dynamically balance the relative values of various characteristics. When combined, these strategies improve the model's ability to perceive and apply crucial information in incoming data. The feature extraction method starts with the output of the ResNet50 architecture, indicated as F. H and W represent the feature map's height and width, respectively, while C specifies the number of channels.

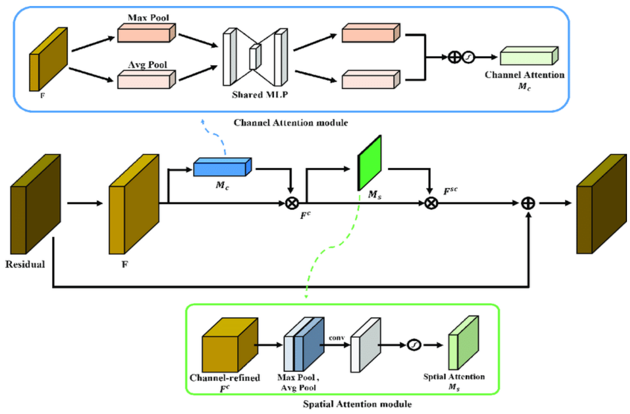

Figure 2.Structure of the convolutional block attention module (CBAM)

The Convolutional Block Attention Module (CBAM) combines channel-wise and spatial attention procedures to improve recovered features. The input feature map's spatial dimensionality is reduced by using average and max pooling layers. The global mean pooling layer for each channel calculates the mean value in the spatial dimensions. At the same time the global maximum pooling layer[36] selects the highest value for each incoming channel. This procedure records differentiable item properties while also combining geographical data. A feature map called Channel Attention Map (CAM) clearly shows the relevance of each channel. A new channel is created using these shared thickness layers. In the channel-refined feature map (denoted by R), where each element is computed on a channel basis, the original feature map F is then generated by multiplying the original feature map F element by element of the CAM.

$$R=CAM\odot F \qquad ----------(1)$$

This improved feature map enables the model to better highlight significant attributes inside it channels. The spatial attention module decompresses the channel-refined feature map into two 2D feature maps, applying maximum and average pooling functions along the channel axis to focus attention on specific regions of the feature map. A spatial attention map is created by multiplying these 2D feature maps with the channel-refined feature map R.The CBAM's final output combines spatial and channel-based attentions. After applying global average pooling to this output and using SoftMax to activate a fully connected layer, the CBAM module's final output is generated.

III. PROPOSED WORK

This study introduces a novel architecture, the Attention-Embedded Residual Network, designed for the recognition of micro-expressions to infer human emotions. The primary objective of this research is to develop a precise and computationally efficient model for the classification of people's emotions based on their micro-expressions. In contrast to conventional CNN networks that assign equal weights to all parameters [49], our proposed model adopts a mechanism wherein each feature is learned and weighted based on its significance. Consequently, highly significant features are assigned higher weights through Attention blocks. These weighted features are then transmitted to deeper layers, thereby facilitating precise and accurate classification.

The conventional CNN model treats all features equally during the learning process, aggregating feature maps from different layers. However, this learning approach poses a drawback as it assigns equal weights to all features, leading to the potential loss of subtle nuances and significant information acquired in the primary layers. In response to this limitation[43], our model introduces a residual architecture that efficiently transmits the crucial information obtained in the initial layers to the deeper layers of the network. This is accomplished through the incorporation of a residual network with an embedded attention mechanism, which selectively weighs significant features higher than others, ensuring the preservation of important information throughout the learning process. This approach supports the effective and precise classification[44] of human micro-expressions.

Figure 3. Illustrates the architectural diagram of the proposed Attention Residual Network. It comprises three Residual blocks connected sequentially, with the size of the convolution kernel gradually decreasing from 7x7 in the first block to 3x3 in the third and final block. An Average Pooling[45] operation is employed at the end to prevent loss of feature information and mitigate over fitting.

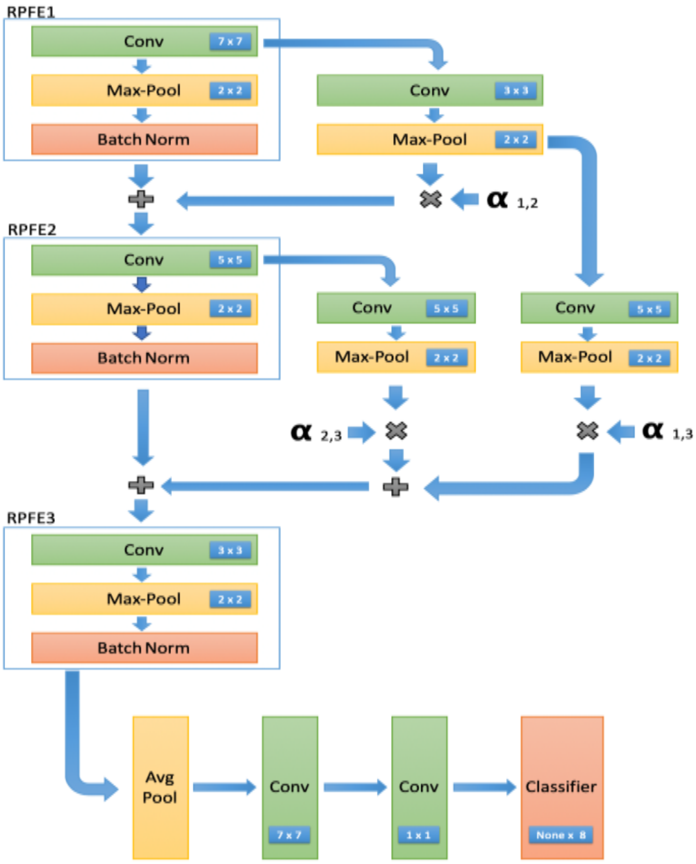

Figure 3.Depicts the architectural design of the suggested model.

IV. RESULTS AND DISCUSSIONS

In such work, 80% of the training dataset is divided for training and 20% for validation[46]. It was also used to evaluate the CBAM model on the test dataset ResNet50.The model was then created and validated using the five-fold cross-validation approach. The accuracy, precision, recall, and overall performance of this model were assessed using AUC metrics. Table 2 provides details on the network's hyper parameters. Table 2 demonstrates that the model was optimized using a variety of algorithms, including Adam and Stochastic Gradient Descent. SGD is utilized for Model B because of its resource efficiency, simplicity, and successful track record [35]. Adam is selected for Model A to take use of its variable learning rate feature, which is useful in handling non-stationary gradients and complicated loss landscapes, leading in better generalization and faster convergence [34]. To create a compromise between training stability and convergence speed, we utilized a learning rate of 0.001. In this model conclusion, the simplicity and resource efficiency of SGD and ReLU make the smaller block size of 16 best suited for Model B and Model C, respectively, but the performance and flexibility of the Adam optimizer best matches the 32 block size of Model A. All of these choices are consistent with the advantages of each optimizer.

Table 2. Various optimizers including Adam, SGD and ReLU were used for the model.

Parameter	Model-A	Model-B	Model-C
Learning Rate	**0.0001**	**0.0001**	**0.001**
Batch Size	**64**	**32**	**16**
Optimizer	**Adam**	**ReLu**	**SGD**
Epochs	**25**	**25**	**25**

In terms of model accuracy and loss schemes, Adam (a) has rapid initial convergence, despite the probability of significant fluctuation during early training periods [36]. In contrast, ReLu (b) and SGD (c) exhibit slower, but more consistent convergence. The low standard deviation of the performance metrics among these optimizers indicates that the model is stable and consistent regardless of which optimization approach is chosen. Figure 4. Receiver operating characteristic (ROC) curve plots for the samples[37], as well as the area under the curve (AUC) scores for each class fit. Figures 5-7 illustrate feature maps for the first, middle, and final 3 layers, confirming that the models detect important image properties and contextual relationships. The feature maps of the first 3 layers show that the premature levels mostly internment low-level components such as edges, textures, and basic forms.

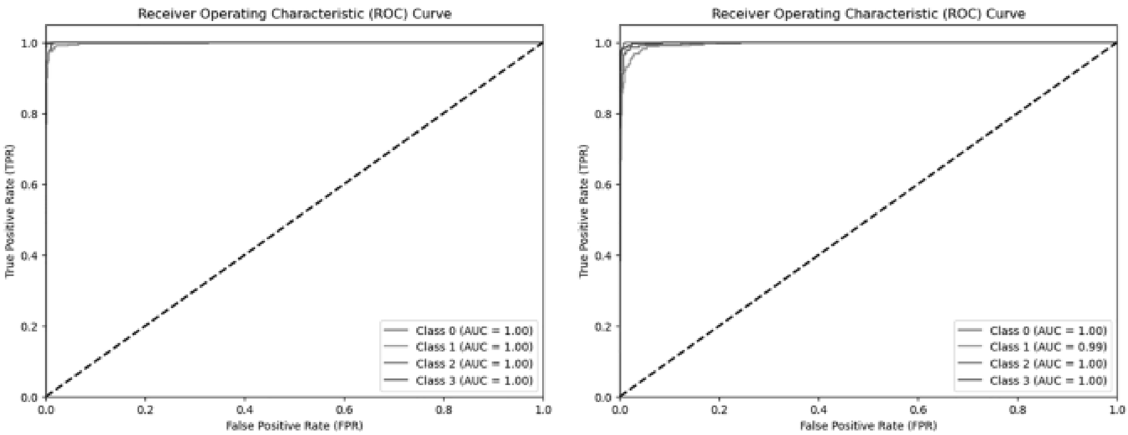

Figure 4. Receiver operating characteristic (ROC) curves for the models,

as well as the area under the curve (AUC) score.

Figures 6 and 7 show how the feature maps grow more abstract as the model network deepens, depicting intricate patterns and regions of brain MRIs. Higher-level elements, such as textures or object-specific forms, have an effect on the deeper levels. Notably[37], the CBAM module de-emphasizes less relevant areas and channels in Figure 6 in favor of regions with significant spatial and channel-wise information, which are anticipated to be more helpful for predictions. A comparative analysis was carried out with state-of-the-art approaches that were already in use in the literature using the same dataset, given the remarkable performance attained. The outcomes, which are shown in Table 4, demonstrate how well the ResNet50-CBAM performed in comparison to other methods. Importantly, as Table 4 shows, the training and evaluation techniques from these previous publications were used to evaluate the ResNet50-CBAM model [39].

Table 4.Demonstrate how well the ResNet50-CBAM performed in comparison to other methods.

Five-fold cross-validation								
Train test split					Model A and B		Model C	
Metric	Model-A	Model-B	Model-C	Average	Mean	Standard deviation	Mean	Standard deviation
Accuracy	98.53	99.59	99.90	98.97	99.35	0.009	98.68	0.014
Recall	99.21	96.19	97.11	97.56	98.54	0.022	96.49	0.021
Precision	98.17	97.79	97.94	98.22	98.90	0.014	97.68	0.017
F1-Score	99.10	96.98	97.91	97.96	98.70	0.018	97.04	0.014
AUC	99.35	97.58	97.93	98.44	99.06	0.013	97.75	0.015

A elimination study was also performed on the model using the additional parameter values and the 80% and 20% train test split estimation approach. Table 4 shows the findings of this experiment. In essence, the more blocks are removed from the model, the poorer the model's accuracy in predicting brain cancers. These were attributed to the smooth integration of all components increasing the effectiveness of the proposed approach[48]. This emphasizes the important role this compound plays in making accurate brain tumor predictions. And according to the results of the two models model A performed better than model B in test split and cross validation. It shows that the combination of parameters of Model A resulted in the most efficient learning process[40]. The Adam optimizer may be one of the contributing components to the Model A's improved performance over others. Adam's ability to adjust the learning rate separately for each parameter is useful for building complex models [36]. SGD, on the other hand, maintains a constant learning rate across iterations for each parameter. Brain tumor classification challenges include high-dimensional and complex feature spaces, and some characterizations may require more subtle training modifications[41]. The adaptive learning rate of this ADAM optimizer dynamically adjusts the learning rates for each parameter individually during training. If large performance improvements[42] are achievable, it seems worthwhile to investigate the effects of changing the block size or using a different optimizer.

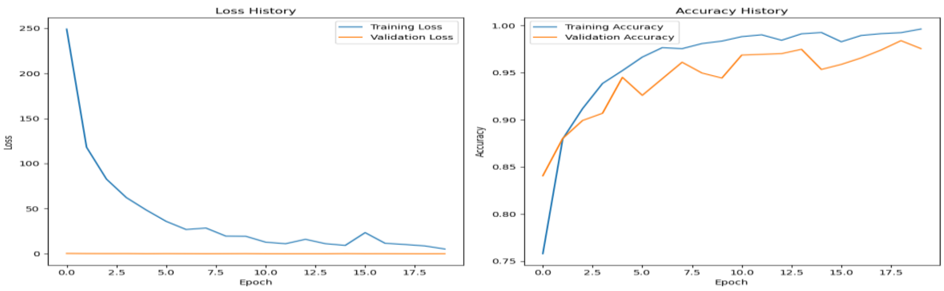

Figure 5. Model – A : Attention mechanism Loss and Accuracy performance

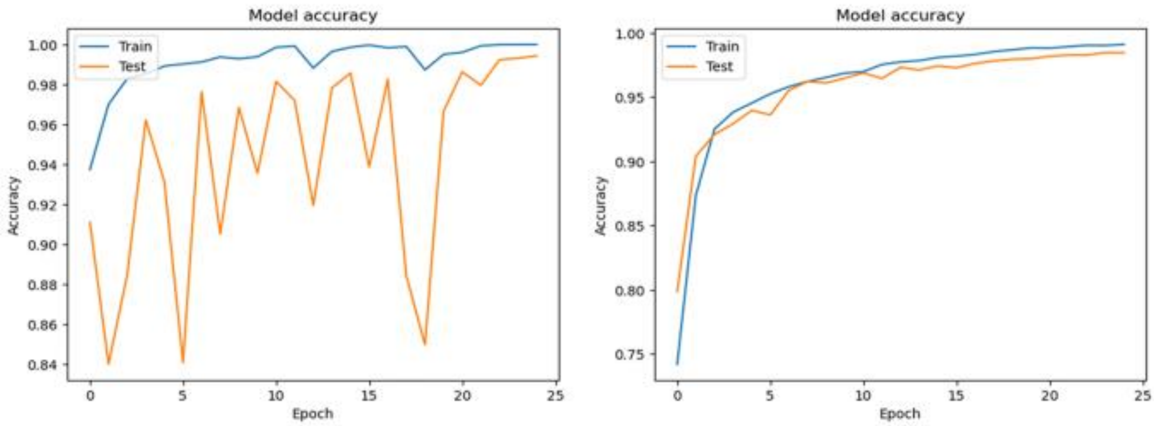

Figure 5. Model – B : Loss and Accuracy performance

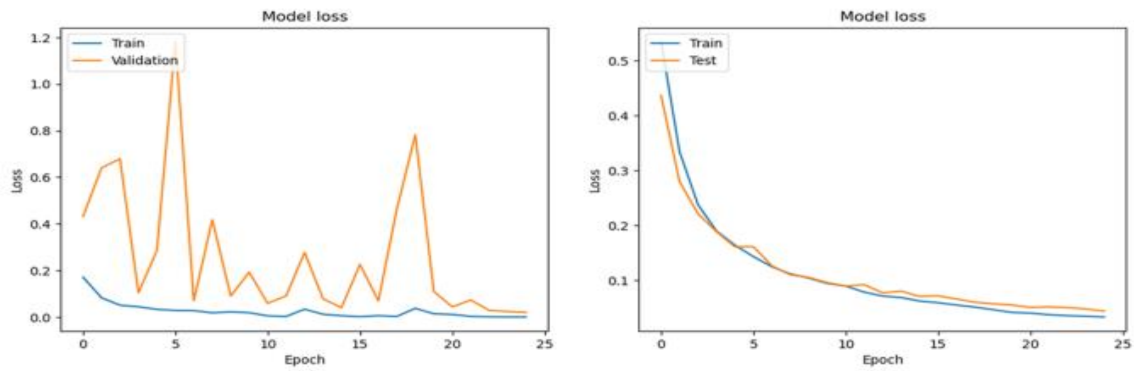

Figure 5. Model – C : Loss and Accuracy performance

The ablation investigation showed that the model's remarkable performance is a result of its attention processes, which allow it to selectively highlight important information while squelching noise. Curiously, the result that ResNet with Channel attention performed better than ResNet with Spatial attention implies that channel-level feature attention may be more advantageous than spatial relationship[49] attention when it comes to brain tumor classification. This emphasizes how crucial it is to properly choose and adjust attention mechanisms according to particular traits. As Table 5 illustrates, ResNet performed better than other previous works, including [37], even though it had the lowest performance in the ablation research.

Table 5. Illustrates, ResNet performed better than other previous works

Evaluation Method	Reference	Architecture	Recall(%)	Accuracy (%)	Precision (%)	F1- Score (%)
80 :20 test split	[2]	CNN EfficientNetB1 ResNet50 CBAM	94.55 95.98 96.0 99. 43	96.5 95.98 95.98 99.0	96.0 95.98 95.98 98.7	96.0 95.98 95.98 99.0
TRAINING & TESTING	[33] [34]	CNN CBAM	95.65 99.15	95.65 98.16	95.97 98.42	95.65 98.29
60 : 20 : 20	[35]	VGG19 CBAM	97.00 98.53	96.0 96.76	97.0 97.38	97.0 97.06
5- FOLD CV	[14]	CNN CBAM	98.40 99.35	98.55 98.65	96.75 98.90	96.75 98.70

Using the ResNet50-CBAM model, multiclass brain tumor classification for MR images was the main focus of this study. The experimental results showed our method's higher performance compared to the most advanced CNN models[50]. Furthermore, the CBAM module helped pre-trained models overcome the difficulties they encountered in accurately acquiring relevant medical brain MRI features, considering the unique characteristics and various imaging modalities of MRI pictures. As seen in Figures 5–7, this module, which included an attention mechanism, concentrated on pertinent features, improving the model's performance.

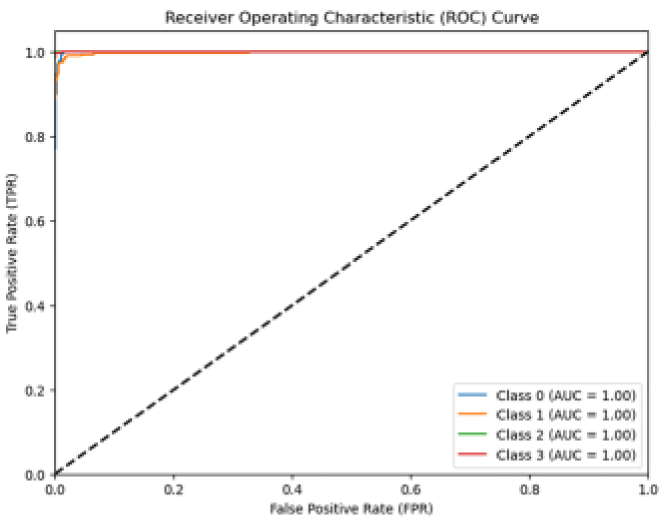

Figure 5.Concentrated on pertinent features and improving the model's ROC performance.

In terms of therapeutic applicability, our results suggest that using the ResNet50 CBAM model for real-world scenarios might lead to quicker and more precise brain tumor identification. This is especially important when treatment plans and patient outcomes depend on early diagnosis. The improved performance of the model could be used by medical practitioners to expedite diagnostic procedures and increase patient care in general. However, when used in actual therapeutic situations, issues like explain-ability and data privacy comes up. Clinicians want to understand how the model makes decisions, so it's critical to do clinical validation later to guarantee efficacy, dependability, and moral integrity. Improving the model's generalize requires addressing data privacy issues, conducting additional evaluations across a range of demographics, and implementing federated learning strategies. To further enhance brain tumor classification models, future research areas should investigate model-agnostic explanation strategies, alternative attention mechanisms, and data pre-processing methods. Furthermore, employing volumetric attention mechanisms to expand this study to 3D MRI creates opportunities for more thorough and intricate feature acquisition.

V. Conclusions

Our research focused on developing a deep learning based technique for accurate classification of brain tumors in clinical imaging. Deep learning is essential for accurately classifying medical pictures. The convolutional block attention technique is employed in the suggested method to efficiently classify several kinds of brain MRI, such as pituitary, meningioma, glioma, and no tumor. Experimental results highlight the excellent performance of the convolutional block attention mechanism framework in brain tumor classification, with an astounding accuracy of 99.43%.Its superiority over baseline techniques demonstrates how well it can detect and categorize brain cancers. Robust pre-processing of the data, clever use of transfer learning, and attention mechanisms are all credited with the exceptional accuracy. It is advised that this strategy be incorporated into doctors' software platforms in light of the impressive results in order to improve clinical decision-making and patient care. In order to improve brain tumor diagnosis even more, we intend to expand our analysis to include more datasets related to brain tumors and investigate a variety of deep learning strategies. It is crucial to recognize the model's computational complexity, nevertheless, as the ResNet50 architecture's incorporation of CBAM attention modules adds more parameters, expands the model's size, and necessitates more memory throughout development. Additionally, CBAM modules include operations like element-wise multiplication, convolution, and global pooling, which raise the computing burden. Developing lightweight deep learning models with attention processes to classify brain tumors may be an important focus of future research. In summary, the ResNet50-CBAM model has great promise to deliver more precise and quick diagnoses in clinical settings due to its adeptness in capturing pertinent features in brain MRI. This can therefore result in better treatment planning and higher patient survival rates. Also, reduced positive outcomes and negative outcomes may occur, possibly reducing patients' fear.

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