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Brain Tumor Classification using MobileNet Convolutional Block Attention Module

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Abstract

Brain tumors are very deadly disease. The first step to investigating brain tumors is CT scan or MRI. The MRI images are then referenced for further investigation. It is very important to locate the tumors effectively. The manual methods of observing tumor location and shape can lead to wrong treatment. Automated methods such as Deep Learning helps to evaluate the type of the tumor and shape of the tumor effectively. In this research we used MobileNet as the pretrained network for the feature extraction process and convolutional block attention model for the visualization. Current study trained four models MobileNet CBAM, MobileNet SE, MobileNet ECA, MobileNet. The model was trained on Figshare dataset which include four classes, glioma, meningioma, no tumor and pituitary. We used 4,557 images to train the model and 1,311 images to test it. The proposed model achieved an accuracy of 95%. The CBAM attention-based visual explainer was used to show where the model was focusing its predictions, which made the model easier to understand. This method is a useful tool in clinical settings where quick and accurate diagnosis is important.

Keywords: Brain Tumor Classification, MobileNet, Convolutional Attention Block, Deep Learning.
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INTRODUCTION

Brain tumor (Younis et al., 2023) is still one of the deadliest diseases every year, affecting thousands of people around the world. The brain tumor(Bahadure et al., 2017) can be classified as malignant or non malignanat. Recent numbers show that the number of people who die from brain cancer has gone up a lot in the last ten years, from about 140,000 to more than 250,000. It can be hard to find brain tumors, especially in their early stages when they can show up in strange shapes and places. Magnetic Resonance Imaging (MRI) is one of the most powerful non-invasive methods of viewing the brain's complex components and helps in detecting brain-related issues at an early stage. Various kinds of brain tumors exist, like gliomas, meningiomas, pituitary tumors, nerve tumors, and embryonal tumors. Each of them can appear very different on MRI scans, further complicating accurate diagnosis. The images are highly detailed but understanding them is not always straightforward. Tumors can look different from one another in their shape, size, and how bright they shine. And even experienced radiologists sometimes have difficulty interpreting the scans accurately. Too few trained medical experts in an area can exacerbate this problem, leading to delays or misdiagnosis. At present, deep learning techniques, particularly CNNs, are a hot tool in the field of medical image analysis(Li et al., 2023; Litjens et al., 2017; Thakur et al., 2024; Wang et al., 2021). The models are trained to identify complex patterns in images that are useful for detecting tumors in MRI scans. Deep-learning-powered automated systems provide highly accurate disease evaluations, aiding doctors in the proper treatment plan strategies. This work is devoted to four types of brain MRI images: that is, glioma, meningioma, pituitary tumor, and no tumor. From slipping into each category to finding them is fraught with their own challenges. For instance, gliomas develop in various areas of the brain and tend to have jagged edges. Meningiomas, while often not cancerous, can compress critical parts of the brain. Pituitary tumors are found next to important structures like the optic nerve and glands that produce hormones.

It is also very crucial to accurately determine if an MRI doesn’t show a tumor to prevent false assumptions. To address these issues, we developed a deep learning framework that adopts a fast and efficient CNN architecture based on MobileNet with a Convolutional Block Attention Module (CBAM). To focus more on the important areas in each scan, the model can accurately identify the tumor. We used 4,557 MRI images to train our model and 1,311 more images to test it. The model was right 94.66% of the time. We also made visual attention maps to show which parts of the images the model looked at when it made decisions. This makes the process easier to understand. Our method strikes a good balance between the model's speed, accuracy, and ease of understanding. Because it's small and works well, it could be useful in real medical settings, especially where powerful computers aren't available. This model could be a helpful tool for diagnosing brain tumors, but more testing and work needs to be done.

LITERATURE REVIEW

The research that has been proposed (Ali et al., 2024) looks at a big problem in medical imaging: how to use MRI scans correctly to find brain tumors. We don't know how well deep learning models work in the real world yet, but they seem to be able to look at pictures of medical conditions very well. One of the biggest problems with this is that MRI data isn't always right. The patient's health, the imaging methods, and the scan technology can all have a big impact on the results. These differences could mean that the model doesn't work well in hospitals. To fix this problem, the researchers used advanced data augmentation and transfer learning.

Their approach is beneficial since it makes the training feel like it's happening in real life. People In order to improve the model's ability to deal with problems that happen a lot in clinical MRI scans, they added distortions like motion blur, noise, and rotation to the training dataset. The team also added similar distortions to test data that was noisy or not very good to see how well the model worked with it. While this study has some positive aspects, it also has many areas that could be improved. One major flaw with the suggested method is that it doesn't consider how much it costs to run the business. This is essential in hospitals and other places where people work with patients, where time and computer power are often short.

This study also doesn't fully explain how changes to the model, such as adding more data and using transfer learning, make it harder to understand. Transfer learning has many advantages, but it's still challenging to make pre-trained models work for medical imaging. This is particularly so when the data used to train the models is very different from the clinical datasets. Lastly, the model might be better at predicting what will happen if you give it more information about the patient, like their age, medical history, or genetic markers. Including this type of information in your predictions may make them more useful for the patient and the situation. The author in (Akter et al., 2024) uses a Convolutional Neural Network (CNN) to find out what kind of tumor it is and a U-Net model to show where the tumor is in MRI scans. One of the best things about this research is that they tried the system on six different datasets. This shows that it works well in a lot of different real-life situations.

CNN was able to get more than 98% of the answers right and only a few false alarms. This means that it was effective at not mixing up healthy tissue with tumors. The U-Net model also did a fantastic job of making the tumors very clear. This can help doctors figure out how to treat them. Overall, this work is important because it helps doctors find brain tumors more accurately and gives them a useful tool. The author in (Nassar et al., 2024) proposed deep learning models and voting classifiers to classify the brain tumor. The author classifies three diseases, such as tumor, glioma, and meningioma.

In deep learning, the proposed study trained different models that include GoogLeNet, AlexNet, SqueezeNet, ShuffleNet, and NASNet. After training all the models, the proposed study uses majority voting on all the trained models. The study claims that the combination of models yields precise outcomes. The dataset used in the study contains 3064 images. The author achieved an accuracy of 99.31 on the majority voting classifier. The author in (Ullah et al., 2024) employed a deep learning and information fusion framework for the classification of brain tumors. In the proposed study, the author applied contrast enhancement to MRI images. Additionally, the author employed a sparse autoencoder to generate new images that would balance the representation of different classes. The author (Balamurugan & Gnanamanoharan, 2023) proposed a study using deep learning and genetic algorithms to classify brain tumors.

The proposed study uses EfficientNetB3 for the feature extraction process. The author chose EfficientNetB3 because of computational efficiency and better accuracy. The genetic algorithm was used to select suitable network parameters. The proposed study achieved an accuracy of 99.56%. The author in (Özkaraca et al., 2023) proposed a transfer learning approach for the classification of brain tumors. The proposed study employed VGG16, DenseNet, and basic CNN architecture. The study also employed k-fold cross-validation.

The proposed study (Sarkar et al., 2023) uses deep learning and machine learning for the classification of brain tumors. In deep learning, it used AlexNet to extract the features of brain tumors. The output is fed into the machine learning classifiers. The proposed work employed various ML models that include Random Forest, Naïve Bayes, BaysNet and sequential minimal optimization (SMO). The proposed strategy achieved an accuracy of around 100% on test data. The study (Kibriya et al., 2023) employed deep learning and handcrafted feature extraction for the classification of brain tumors.

VGG16 was used along with GLCM (gray-level co-occurrence matrix) as a feature extractor. For the classification task, the author selected SVM and KNN. The proposed work achieved an accuracy of 99%. The author in (Athisayamani et al., 2023) proposed a novel algorithm called the Enhanced Chimpanzee Optimization Algorithm (EChOA). The proposed work employed a pretrained model, ResNet-152. The proposed study achieved an accuracy of 98.85%. The author in (Kurdi et al., 2023) proposed Harris Hawks Optimization CNN. The MRI images were first preprocessed, and the noise was removed. The candidate region process was applied for the tumor region. The suggested work achieved an accuracy of 98%. The author in (Asiri et al., 2023) worked on different ML algorithms that include SVM, Random Forest, and Naïve Bayes. In the proposed study, the author has worked on a small dataset of brain tumor images that includes two classes: yes and no. The size of the dataset is 253 images. The study (Islam et al., 2023) utilizes transfer learning approach.

The proposed study uses four pre-trained models that include VGG19, MobileNet, DenseNet121 and InceptionV3. The proposed approach achieved an accuracy of 99.60%. The author (Anaya-Isaza et al., 2023) in made a comprehensive review of different neural networks like InceptionResNetV2, InceptionV3, DenseNet121, Xception, ResNet50V2, VGG19, and EfficientNetB7. The trained models produced around 97%. The study (Ahmmed et al., 2023) utilized transfer learning that included ResNet50 and InceptionV3. The proposed work used two datasets. The first dataset includes four classes, while the second dataset includes two classes.

The work used regularization and the Nadam optimizer. The accuracy achieved was 97.68% in four classes and 99.62% for tumor positive and 100% for tumor negative. The work in (Aloraini et al., 2023) used a hybrid approach that comprised CNN for feature extraction and transformer for attention mechanism. The proposed work employed two datasets: Brats 2018 and Figshare. The proposed work achieved an accuracy of 96.75% and 99.10%. The proposed work in (Rasheed et al., 2023) adopted CNN and image enhancement techniques for the classification of brain tumors.

The image enhancement techniques include Gaussian-blur-based sharpening and Adaptive Histogram Equalization using CLAHE. The proposed work achieved an accuracy of 97.84%. The author in (Hussain & Shouno, 2023) introduced an explainable deep learning approach. In this work, the author used visualization techniques that include CAM, Grad CAM, and Grad CAM++. For the feature extraction process, VGG19 was chosen to train the model. The model was trained on VGG19 from scratch and VGG19 transfer learning. The author claims VGG19 using transfer learning performed better.

MATERIALS AND METHODS

Figure 1 shows the CBAM attention map superimposed on a brain MRI image, which makes it easier to understand and see how the model works. A color-coded attention heatmap is placed on top of the original grayscale brain MRI. Red areas show high attention (i.e., the likely location of the tumor). Green and yellow show moderate attention. Blue means little or no attention. The model has really focused on the bright red/pink ring in the upper-right part of the brain, which is where a suspicious lesion or tumor might be. This visualization is an important tool for explainable AI (XAI) because it shows radiologists or doctors which part of the image affected the model's decision.

Table 1 shows a detailed breakdown of the architecture of a deep learning model that uses MobileNet with CBAM (Convolutional Block Attention Module) and a custom classification head to classify brain tumors.

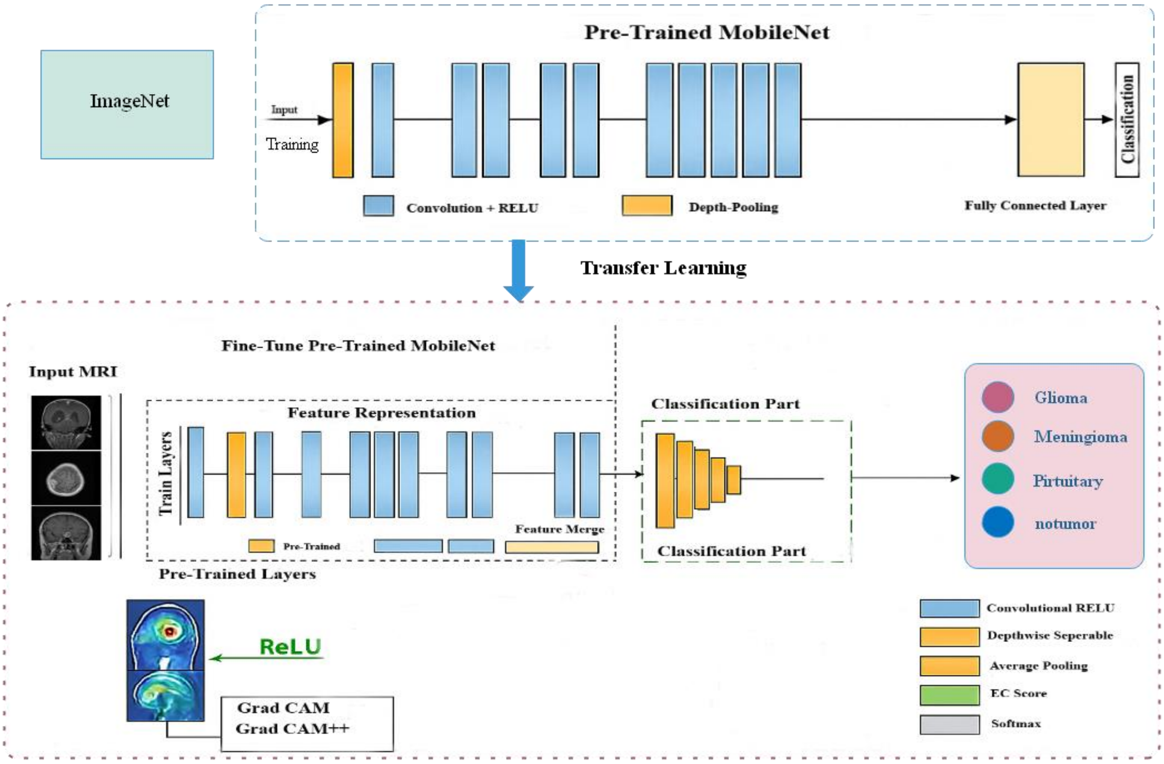


Figure 1.
Proposed Model

Table 1.
Model Summary

Layer Name	Type	Output Shape	Parameters	Description / Notes
input_60	InputLayer	(None, 224, 224, 3)	0	Input layer for RGB image
mobilenet_1.00_224	Pre-trained MobileNet	(None, 7, 7, 1024)	3,228,864	Convolutional feature extractor (frozen)
global_average_pooling2d_54	GlobalAveragePooling2D	(None, 1024)	0	Channel-wise mean used for CBAM channel attention
global_max_pooling2d_25	GlobalMaxPooling2D	(None, 1024)	0	Channel-wise max used for CBAM channel attention
reshape_50	Reshape	(None, 1, 1, 1024)	0	Reshaping GAP output to match Conv2D format
reshape_51	Reshape	(None, 1, 1, 1024)	0	Reshaping GMP output
dense_124	Dense (shared in CBAM)	(None, 1, 1, 128)	131,200	Channel reduction (1024 → 128)
dense_125	Dense (shared in CBAM)	(None, 1, 1, 1024)	132,096	Channel expansion (128 → 1024)
add_25	Add	(None, 1, 1, 1024)	0	Element-wise sum of GAP and GMP pathways
tf_op_layer_Sigmoid_27	Sigmoid Activation	(None, 1, 1, 1024)	0	Sigmoid output for channel attention

multiply_25	Multiply	(None, 7, 7, 1024)	0	Feature recalibration via attention mask × feature map
global_average_pooling2d_55	GlobalAveragePooling2D	(None, 1024)	0	Pool recalibrated features to vector
batch_normalization_45	BatchNormalization	(None, 1024)	4,096	Normalize features before Dense layers
dense_126	Dense	(None, 256)	262,400	Fully connected layer with ReLU
dropout_44	Dropout	(None, 256)	0	Regularization to prevent overfitting
dense_127	Dense (Softmax Output)	(None, 4)	1,028	Output layer: 4 tumor classes

RESULTS & DISCUSSION

Figure 2. shows different brain MRI images with data augmentation. Data augmentation techniques help to increase the size of the dataset for better training accuracy.

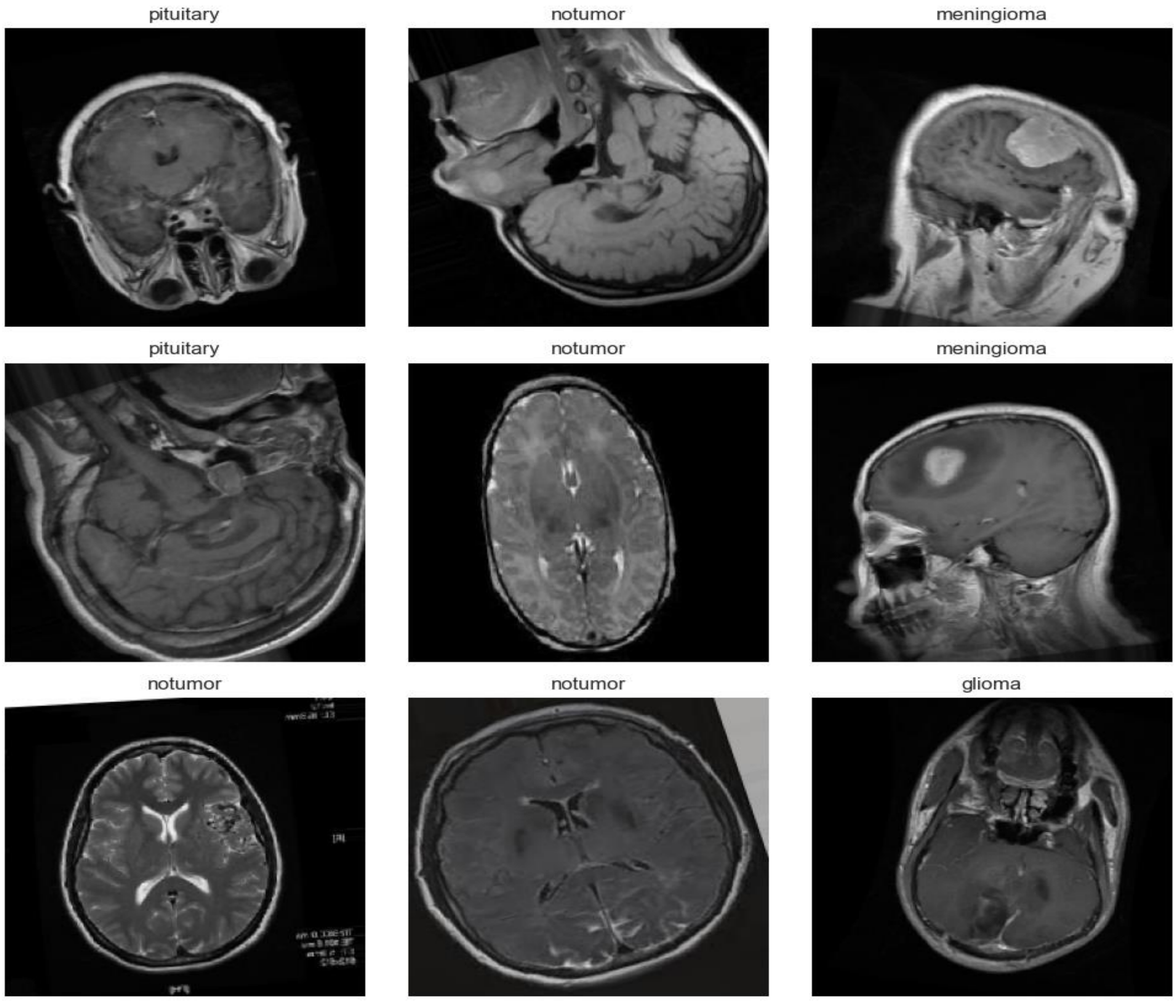
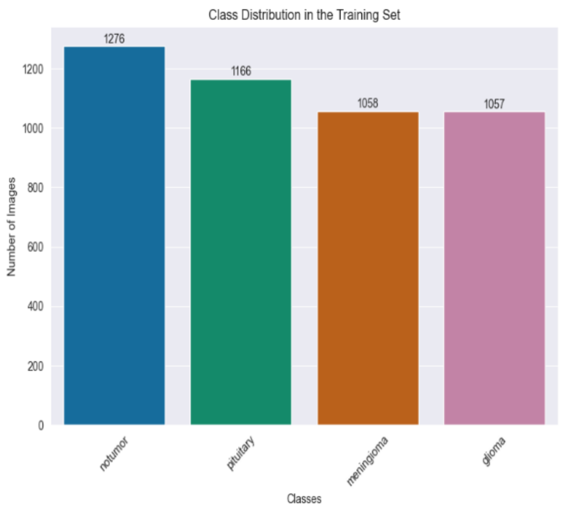


Figure 2.
Image Augmentation

Figure 3. shows the graph of the training set which include a total of 4557 images divided in four classes. Figure 4. Shows the graph of test set which includes a total of 1311 images.



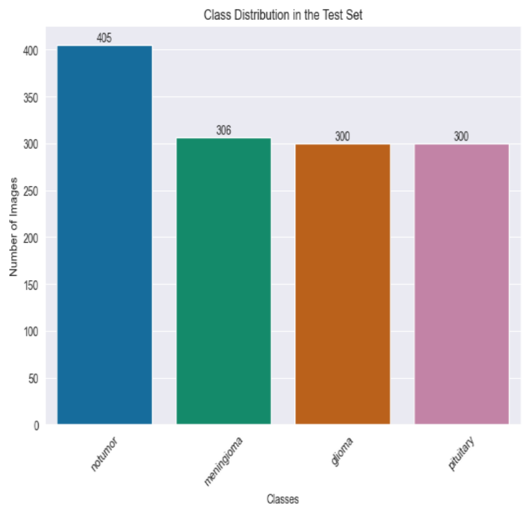
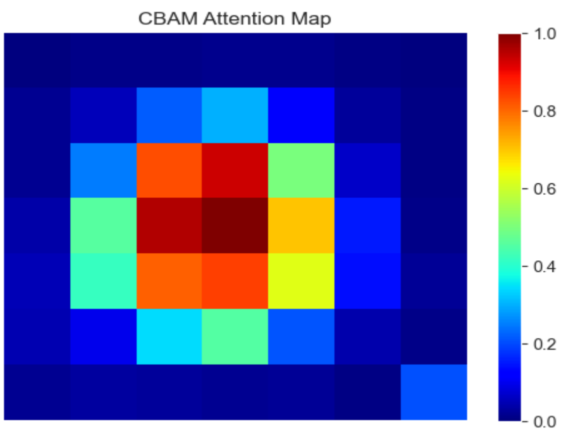


Figure 3.
Training Set

Figure 4.
Test Set

Figure 5 is a heatmap that shows the spatial attention weights that the Convolutional Block Attention Module (CBAM) made during inference. The attention map is a two-dimensional matrix where each cell shows how important that part of the input feature map is. The color scale on the right goes from 0 (dark blue) to 1 (dark red), with higher numbers showing more attention or importance. The red and orange areas in the middle show that the CBAM module thinks they are very useful for classification (for example, where the tumor is likely to be).

This map shows where the model is "looking" in the feature map when it makes a choice. Figure 6 shows the CBAM attention map superimposed on a brain MRI image, which makes it easier to understand and see how the model works. A color-coded attention heatmap is placed on top of the original grayscale brain MRI. Red areas show high attention (i.e., the likely location of the tumor). Green and yellow show moderate attention. Blue means little or no attention. The model has really focused on the bright red/pink ring in the upper-right part of the brain, which is where a suspicious lesion or tumor might be. This visualization is an important tool for explainable AI (XAI) because it shows radiologists or doctors which part of the image affected the model's decision.



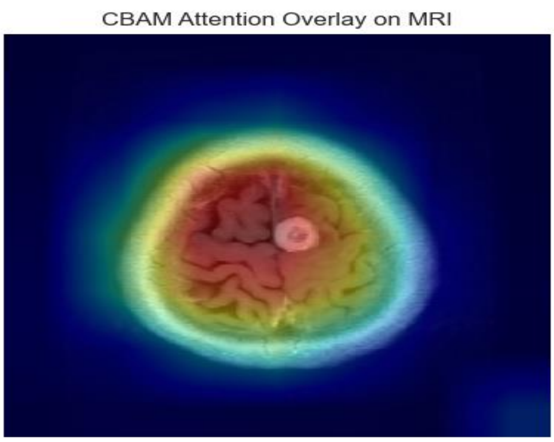


Figure 5.
CBAM Attention Map

Figure 6.
CBAM Attention Overlay

Figure 7-10 shows the training accuracy and test accuracy, training loss and test loss. The study used early stopping in training the dataset. Different models were trained which included MobileNet CBAM, MobileNet SE, MobileNet ECA and MobileNet.

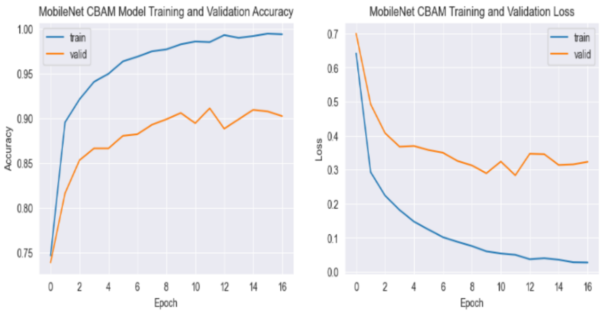


Figure 7.
MobileNet CBAM Training and Validation Accuracy

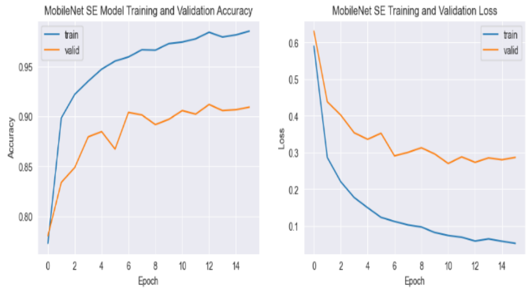


Figure 8.
MobileNet SE Training and Validation Accuracy

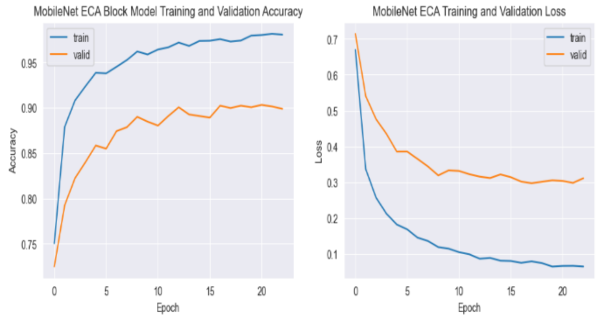


Figure 9.
MobileNet ECA Training and Validation Accuracy

Figure 10.
MobileNet Training and Validation Accuracy

Figure 11-14 shows the confusion matrix of different models.

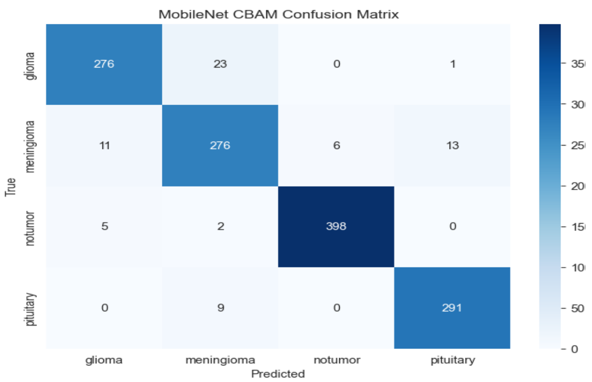


Figure 11.
Confusion Matrix of MobileNet CBAM

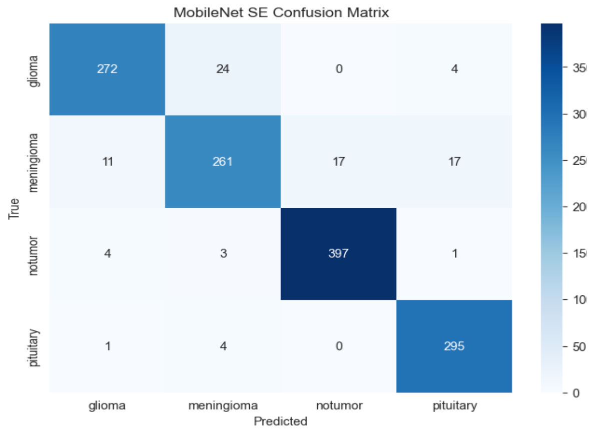


Figure 12.
Confusion Matrix of MobileNet SE

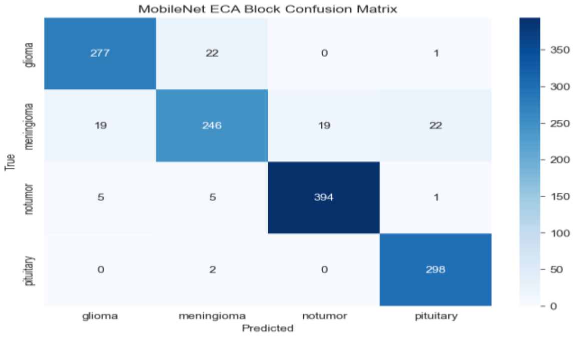


Figure 13. Confusion Matrix of MobileNet ECA

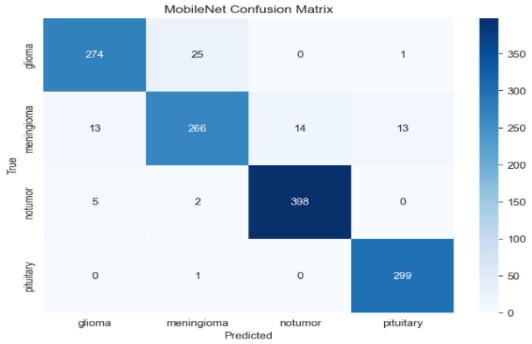


Figure 14. Confusion Matrix of MobileNet

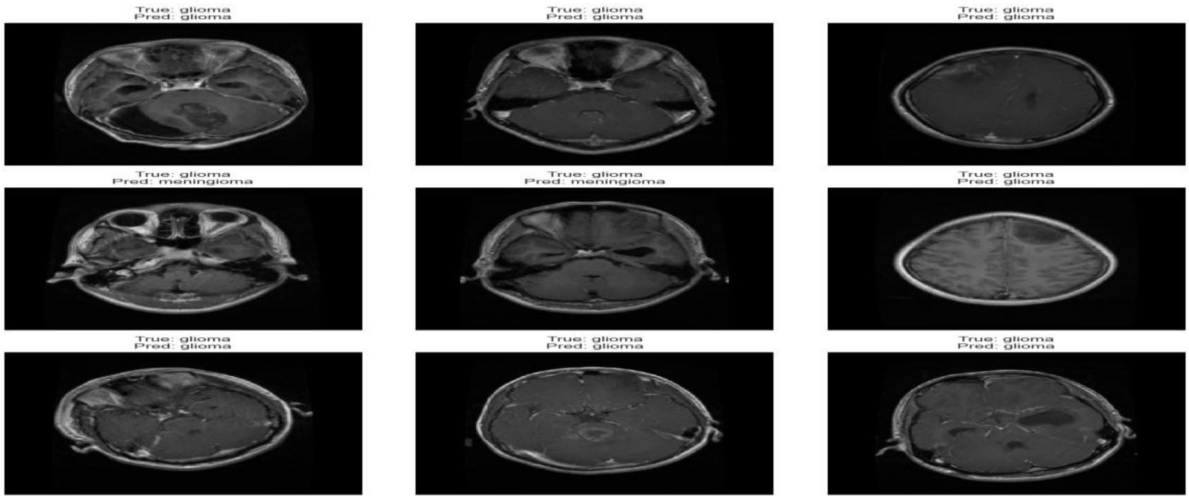


Figure 15.
Predictions

Figure 16. is the representation of Grad-CAM visualizations of how the proposed MobileNet-CBAM model can be used to classify brain tumors. The attention heatmap on top of the original MRI in each image shows the areas that had the biggest effect on the model's prediction. Above each sample, you can see the true label, the predicted class, and the confidence score. The model correctly finds glioma and meningioma cases, with a strong focus on areas around the tumor, showing that it is easy to understand and reliable for diagnosis.

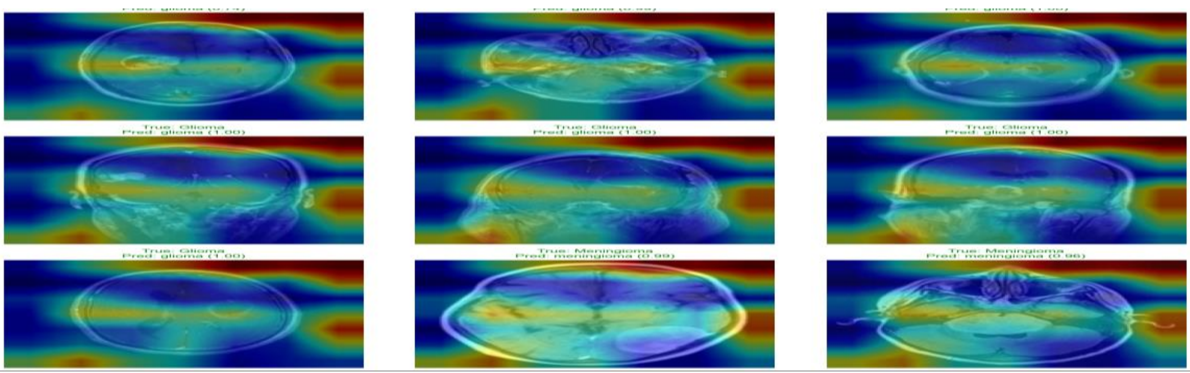


Figure 16.
Grad-CAM Visualization

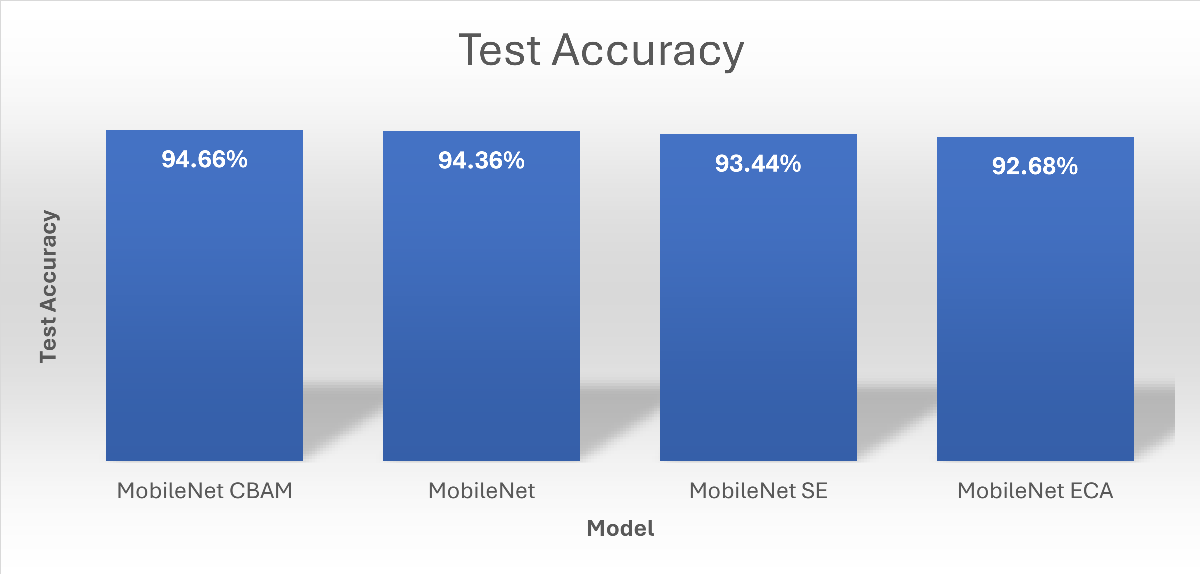


Figure 17.
Model Accuracy

CONCLUSION

In this study we proposed a model that uses the MobileNet and Convolutional Block Attention Module to classify various MRI brain images. The MobileNet architecture is a lightweight pretrained model that was used for the feature extraction process. The CBAM block was used as the attention mechanism. The model was able to improve its focus on the most important features by combining a pre-trained MobileNet architecture with the Convolutional Block Attention Module (CBAM). This made classification easier to understand. We also used visualization tools like Grad-CAM and Grad-CAM++ to make attention-based heatmaps, which helped us better understand how the model made decisions. The proposed method was more accurate and better at finding things than baseline models. This shows how useful it is to add attention mechanisms to lightweight convolutional networks. This mix of performance and openness makes the model better for use in clinical settings, where being able to trust and understand the results is very important. In the end, the model looks like it could help radiologists find brain tumors faster and more accurately, which will help people trust AI-assisted diagnostics.

DECLARATIONS

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Authors' contributions: Each author participated equally to the creation of this work.

Conflicts of Interests: The authors declare no conflict of interest.

Consent to Participate: Yes

Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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