# A Hybrid Deep Learning Framework Integrating CBAM Attention and MobileNetV3 for Accurate Brain Tumor Detection

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**Abstract**
Brain tumors are a life threatening health problem with high mortality rate and thus require proper detection procedures. This study will put forward a hybrid deep learning model to classify brain tumors using MRI scans. The algorithm combines MobileNetV3 to extract features effectively with a Convolutional Block Attention Module (CBAM) that adds channel-wise and spatial attention to emphasize diagnostically relevant areas. A Multilayer Perceptron (MLP) classifier, which consists of two hidden layers, is used to make a final classification of four classes: glioma, meningioma, pituitary tumor, and healthy tissue. The accuracy with a dataset of 7,000 MRI scans shows 98.93 percent with precision of 98.96 percent and recall of 98.93 percent.

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**Keywords:** Brain Tumor (BT), Convolutional Block Attention Module (CBAM), Multilayer Perceptron (MLP), MobileNetV3

## Introduction

A brain tumor is defined as the abnormal increase in the number of cells in the brain tissue. The condition is linked with high mortality rates among the pediatric population and adults. Brain tumors can be broadly classified into two groups such as benign and malignant. Benign tumors are non-cancerous and grow at a slower pace and they never invade the adjacent tissues and other parts of the body. Contrastingly malignant tumors are cancerous and can spread to other parts. Primary brain tumors begin in the brain or its surrounding areas. The expression tumor is usually used to mean unregulated growth of cells in the cranial cavity or in the central spinal canal. Tumors are further classified into intracranial tumors and extracranial tumors, wherein the tumor develops directly within the brain and in a different part of the body respectively before being metastasized into the brain or the spinal cord. The problem of brain tumors is a very serious issue in the fields of oncology and neurology. Conventional methods of detection are based on visual analysis of medical images by radiologists or neurologists e.g., MRI scans. Yet, these traditional methods may be subjective and strongly relying on the experience of the clinician. The new technology such as machine learning (ML) and deep learning (DL), allows detecting the tumor in real time with high accuracy and therefore, helps the medical practitioners make more informed decisions. The tumor in the brain may badly interfere with the normal functioning of the brain. The typical symptoms are headaches, seizures and changes in the cognitive abilities or personality. Moreover, the neurological impairments can be observed and it depends on the size and the exact location of the tumor in the central nervous system.

In this research paper image augmentation and pre-processing techniques are used in the first stage to increase the diversity and quality of the input information. A Convolutional Block Attention Module (CBAM) is used to enhance the feature representation and attention on the diagnostically relevant areas. CBAM applies channel-wise attention and spatial attention sequentially, which enables the model to focus on informative features and ignore irrelevant ones. After this attention-based boosting, feature extraction is carried out with the help of MobileNetV3 architecture that is a lightweight and efficient convolutional neural network which is targeted to operate in resource intensive settings. MobileNetV3 uses depthwise separable convolution and neural architecture search to learn high-level semantics features at a low computational cost. Salient features are then obtained based on these refined and extracted feature maps and then used to build a classification model based on a Multilayer Perceptron (MLP). The MLP is able to learn the complex non-linear relationships in the data in order to predict accurately.

The objective of this research paper is

- To Apply Convolutional Block Attention Module (CBAM) into the proposed framework so that the model would selectively focus on the most informative features (both spatial and channel-wise) in the dataset provided.
- To extract deep features of brain MRI images using a pre-trained MobileNet architecture through transfer learning.
- To build a brain tumor detection predictive system based on the Multi-layer Perceptron (MLP) as the classification model.

The rest of this paper is structured as below. Section 2 has a literature review related to it. Section 3 explains the materials and methods used in this research. Lastly, Section 4 presents the experimental findings and a discussion of the results.

## Literature Survey

Yeafi et al. (2025) have proposed a deep learning model DSNet to segment brain tumors and predict patient survival based on multimodal MRI. They use a 3D U-Net framework that combines adversarial learning, dynamic convolution, and attention to tackle the heterogeneity and complicated morphology of tumors. The model was tested on BraTS datasets and had high Dice similarity scores on tumor regions. Prediction of survival is further possible through a Random Forest-based module that uses volumetric features extracted. A user-friendly interface increases clinical utility, which facilitates the use in real-life healthcare practice [1]. Appiah and colleagues also conducted a related study in which they compared a Proper Orthogonal Decomposition (POD) with a CNN to traditional deep learning models to achieve efficient brain tumor detection. Their POD-CNN method minimized the computational cost without compromising the predictive ability with accuracy of 95.88 and a 3 times lower computational cost compared to the regular CNNs [3]. Kavita et al. introduced a brain tumor detection method that would use digital twins, IoT-based cloud storage, and machine learning. Digital twin-enabled devices in their scheme of things record the MRI images, which are centrally stored with the help of the IoT systems. Particle Swarm Optimization (PSO) is used to perform feature selection and then, it is classified by CNN, SVM and Extreme learning machines (ELM). Their results emphasize the power of CNN to detect abnormal tissues in MRI images [5].

A number of deep learning models have been studied to analyze brain tumors. One paper came up with three models: a 13-layer 2D CNN, a 9-layer 2D CNN, and a CNN-LSTM hybrid. MRI medical images were used to train these models. Comparative findings revealed that an ensemble model performed better than each model alone [4]. Jakhar et al suggested a Multi-scale Fractal Feature Network (MFFN) based on deep learning methodology to detect brain tumors. Their approach uses pixel-wise segmentation of the images that is followed by fractal residual learning and multi-scale feature extraction to enhance sensitivity and accuracy. Multi-level segmentation is useful in maintaining the tumor-related data and minimizing false regions which leads to high accuracy of the model. This method was tested on the Cancer Imaging Archive (TCIA) data set with 5-fold cross-validation with the segmentation accuracy of 94.66 sensitivity of 94.42 and specificity of 92.81 [6]. In another study IRNetv which is a CNN-based deep learning brain tumor detector was proposed. This architecture has inception modules and residual connections to learn a variety of features on medical images with different convolutional filter sizes and kernel sizes. Two publicly available MRI datasets comprising 4,600 and 253 brain images, respectively were used for training. Three optimizers, Adam, RMSProp, and SGD, were compared using different batch sizes (16, 32, and 64). The Adam optimizer with a batch size of 64 was the best with a classification accuracy of 99% [7].

Priya et al. developed a hybrid deep learning architecture to classify brain tumor in MRI data by using AlexNet with Gated Recurrent Unit (GRU) network. They use a non-local means filter in their method to pre-process images. AlexNet learns spatial features through convolutional layers, and the GRU learns sequential dependencies and eliminates the vanishing gradient issue. Generalization and overfitting are enhanced by tuning hyperparameters. The model categorizes the MRI scans into four groups, which are glioma, meningioma, pituitary tumor, and normal tissue. This hybrid structure obtained an accuracy of 97, precision of 97.63, recall of 96.78 and F1- score of 97.25% [8]. Prasanthi and coworkers provided a comparative study of a few developed deep learning models that include DenseNet121, EfficientNetB7, InceptionResNetV2, InceptionV3, ResNet50V2, VGG16, and VGG19 to classify MRI images. They also created a hybrid CNN model which achieved 96.63 precision. They found that VGG19 and InceptionResNetV2 are especially effective in the detection of glioma tumors. The hybrid model was better in general performance and reliability, indicating the possibility of combining various deep learning structures to detect brain tumors with high accuracy and promptly [9]. Singh et al. came up with a new CNN model named BrainNet, which is used to accurately classify brain tumor MRI images. This model will deal with the problems related to the irregular tumor shapes and the lack of professional radiologists in developing countries. BrainNet was tested in comparison with some pretrained transfer learning models, such as VGG13, VGG16, VGG19, InceptionResNetV2, and SqueezeNet. The suggested architecture resulted in a precision of 94.75, a training accuracy of 99.96 and a testing accuracy of 97.71 [10].

The brain tumor detection and classification model developed is a deep learning-based sequential model that uses MRI images. The process will be carried out in two phases; initially to differentiate between neoplastic and non-neoplastic brains, and later to categorize the medical images. Adam, Nesterov Momentum, RMSProp and Adagrad were four optimizers that were experimented with. Adam performed the best in tumor versus non-tumor differentiation and had a 100 percent training accuracy and 98 percent on both the validation and the test set. Nesterov Momentum was most effective in separating three types of tumors, training accuracy 100 percent, validation/testing accuracy 92 percent and in a third classification task, training accuracy 100 percent and validation/test accuracy 95 percent [11]. Agarwal and colleagues had a hybrid approach to the early detection of brain tumors. They used Optimized Discrete-Time Wavelet-based Contrast Histogram Equalization (ODTWCHE) to improve the images of low contrast in MRI. Following contrast improvement, a transfer learning Inception v3 model was used for tumor classification. The suggested approach has been tested in contrast to AlexNet, VGG-16, DenseNet-201, VGG-19, GoogLeNet, and ResNet-50 with the accuracy of 98.89 [12]. A model suggested by Anantharajan et al. is a blend of machine learning and deep learning. To improve the quality of MRI images, an Adaptive Contrast Enhancement Algorithm (ACEA) and a median filter are used to preprocess images. Fuzzy C-Means clustering is used to perform segmentation, and feature extraction using GLCM is done using energy, mean, entropy and contrast. An Ensemble Deep Neural Support Vector Machine (EDN-SVM) classifier is used to differentiate between abnormal and normal brain tissues. A model constructed based on publicly available MRI images has an accuracy of 97.93, specificity of 98 and sensitivity of 92 [13].

Lamba et al. used an open-source MRI dataset to train their model. Standardization and expansion of the data were done with the help of data augmentation and transfer learning was conducted using VGG-16 architecture to extract deep spatial features. Linear SVM was used next to improve the performance of the classifier. The VGG-16 and SVM model showed that the model had an accuracy of 98.87 percent, a precision of 99.09 percent, a recall of 98.73 percent, a specificity of 99.02 percent, and an F1-score of 98.91 percent [14].

Mohammed H. et al. built a CNN model with 4,000 MRI images, which have been downsized to 224x224 pixels. Their model achieved an excellent accuracy of 97.28, which shows that deep learning is effective in classification of brain tumors. The results also suggested that generalization of the model was enhanced with an increase in the size of data. The deep learning model was trained through 60 epochs to improve accuracy and findings validated that the deep learning model was more accurate and faster than the traditional methods [15].

Ramtekkar et al. proposed improved methods of detecting brain tumors. To improve the quality of images, they used a compound filter based on Gaussian, mean and median filters. Grey Level Co-occurrence Matrix (GLCM) techniques were used to extract the feature and a CNN-based classification model was used with an accuracy of 98.9% [16]. Bhagyalaxmi and colleagues have made a comparative study of both feature extraction and optimization method. They adopted a hybrid CNN feature with SVM and an ensemble learning method to classify medical images. They used Mask-RCNN with DenseNet-41 and GoogleNet [17]. Rasool et al. compares machine learning and deep learning methods with each other in detecting brain tumors. They used CNN, VGG16, ResNet50, and hybrid architectures as DL models, training them on publicly available datasets (BraTS and Figshare). First steps were image preprocessing and augmentation. The hybrid DL model offered the best accuracy of 95% indicating that it can extract spatial and textural information out of MRI data to decrease diagnostic delays and aid clinical decision-making [18].

Wankhede et al. used MRI images to forecast the presence of glioblastoma brain tumor and their results were based in a hospital setting. Preprocessing was done by subtracting the mean intensity value and standard deviation of the brain region and noise reduction by bilateral filters. Automatic tumor segmentation was done using

Modified Fuzzy C-Means Clustering (MFCM). They were found to have significant features that distinguished the high and low-grade glioblastoma multiforme (GBM). The authors introduced Multilevel Layer Modeling method in a Faster R-CNN framework, which they termed as MLL-CNN, in their predictive model [19]. Mathivanan et al. used transfer learning networks, such as ResNet152, VGG19, DenseNet169, and MobileNetv3 to classify brain tumors based on MRI images. They performed a 5-fold cross-validation and image enhancement to the MRI data. MobileNetv3 had the highest accuracy of 99.75, but the research failed to show the generalizability of the model with different datasets [20].

## Methods and Materials

In the case of brain tumor prediction using MRI scans a dataset at the Kaggle online storage, which includes non-cancerous and pathological images is used. There were 7,000 MRI scans systematically divided into the training and testing subsets, where 80 percent of the total was used to train the model and the remaining 20 percent were to be used to test the model. The medical imaging collection involves four different diagnostic categories: glioma, meningioma, pituitary tumor and no tumor. Gliomas grow in the glial cells in the brain and meningiomas grow in the meninges which are the protective membranes of the brain and spinal cord. The pituitary type includes scans with tumors in the pituitary gland which could interfere with hormone regulation. The no tumor category can be used as a control which is composed of images of people who had no apparent anomalies. This is a multiclass dataset consisting of four classes which can be used in multiclass classification tasks as well as in transfer learning tasks. The split of training and testing provides the unbiased evaluation of the model and reduces the risk of overfitting.

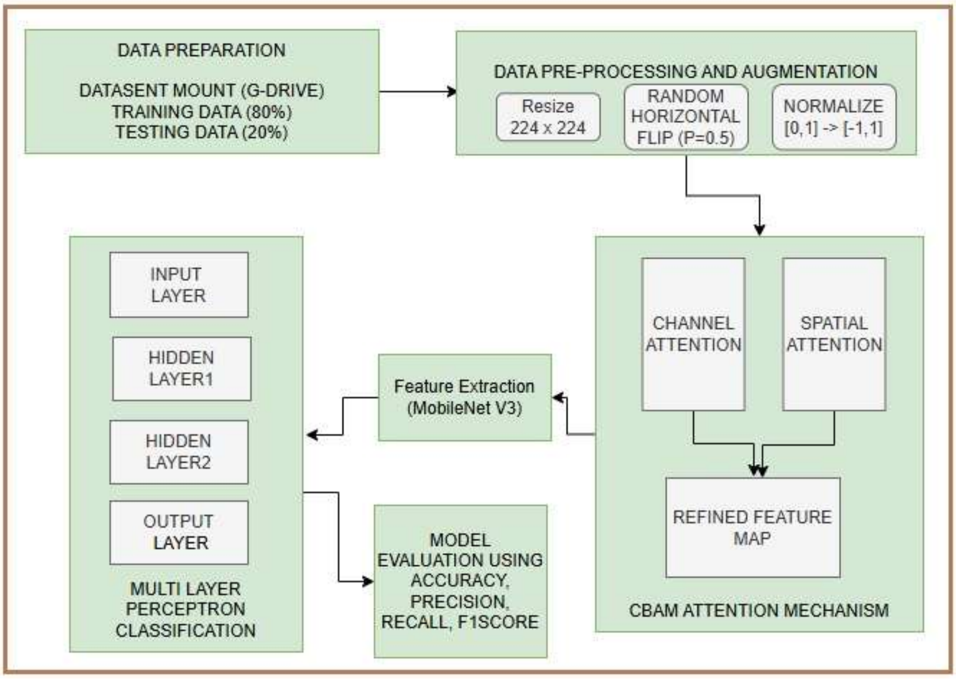


**Figure 1:** Proposed Methodology Architecture

**3.1. Flow of algorithm**

**Step 1: Data Pre-processing**

**Input**: The MRI dataset comprises four diagnostic classes: glioma, meningioma, pituitary tumor and healthy controls without tumor.

Resize each image to fixed dimensions H×W (224 X 224)

Image Normalization: I255

Apply image augmentation

**Step 2: Feature Extraction using transfer learning such as MobileNetV3**

A pre-trained MobileNetV3 architecture serves as the feature extraction backbone, with its classification head removed. For an input image x, this encoder generates a high-dimensional feature representation.

$F_{MobileNetV3}$=MobileNetV3 (x)

**Step 3: Attention Refinement Using CBAM**

**3.1 Channel Attention Module (CAM)**

The mechanism identifies significant feature channels, such as textures and edges, by applying both average and max pooling operations across spatial dimensions to capture global scene characteristics alongside local pattern details.

$M_c (F) = \sigma (MLP(avgpool (F) + MLP(maxpool(F)))$

$F_{cam} = M_c (F_{MobileNetV3}) X F_{MobileNetV3}$

$MLP(x) = W_2. ReLU (W_1. X + b1) + b2$

Where $W_1$ is reduces the dimensions, $W_2$ is restore original channel dimension, b1 and b2 are biases and ReLU is the activation function.

**3.2 : Spatial Attention Module (SAM)**

The module determines the most relevant spatial locations within an image for model attention. This is accomplished through two-dimensional pooling operations applied across channel dimensions, followed by a 7×7 convolutional layer.

$M_s(F) = \sigma\ (f^{7x7}\ (\ AvgPool\ (F_{cam}\ )\textbf{;}\ MaxPool\ (F_{cam}\ )))$

The feature map becomes $F_{cbam} = M_s\ (F)\ X\ F_{cam}$

The extracted feature representations become increasingly attentive to diagnostically significant regions within the pulmonary anatomy.

**Step 4: Global Average Pooling**

Converts the feature map $F_{cbam} \in R^{c\ X\ H\ X\ W}$ to a 1D vector by averaging across spatial dimensions

$F_{gap} = 1H.Wi=1Hj=1WF_{cbam\ (i,j)}$

**Step 5: Multi-Layer Perceptron (MLP) Classifier**

The 1D feature vector is passed into a fully connected feedforward neural network

Hidden Layer

$H1 = \phi(W1f+b1)$

Where $\phi$ is a non-linear activation function and $W_1$, $b_1$ are learnable weights and biases.

Output Layer

$\bar{Y} = softmax\ (W_2h_1 + b_2)$

**Step 6: Assess model performance using metric such as accuracy, precision, recall and f1 score**.

The proposed approach as shown in above figure 1 is based on a six-step pipeline of the image classification. Phase 1 entails the mounting of the dataset on Google drive and the division of the dataset into training and testing parts. Phase 2 implements preprocessing such as resizing to 224 224 pixels, random horizontal flipping as image augmentation and ImageNet statistics normalization to model input distribution. Phase 3 incorporates both the Convolutional Block Attention Module (CBAM) that sequentially enhances feature maps with channel and spatial attention to highlight informative parts and deemphasize irrelevant parts. Phase 4 uses a trained MobileNetV3-Large as a backbone feature extractor, which produces 960-dimensional feature vectors based on attended feature map. The phase 5 involves a Multi-Layer Perceptron (MLP) classifier with two hidden layers of 512 and 256 neurons that use both batch normalization and dropout regularization. The network is trained on 10 epochs with Adam optimization and cross-entropy loss. Phase 6 measures the model performance based on accuracy, precision, recall and F1-score metrics and produces line graphs to visualize the trends of training and the final classification performance.

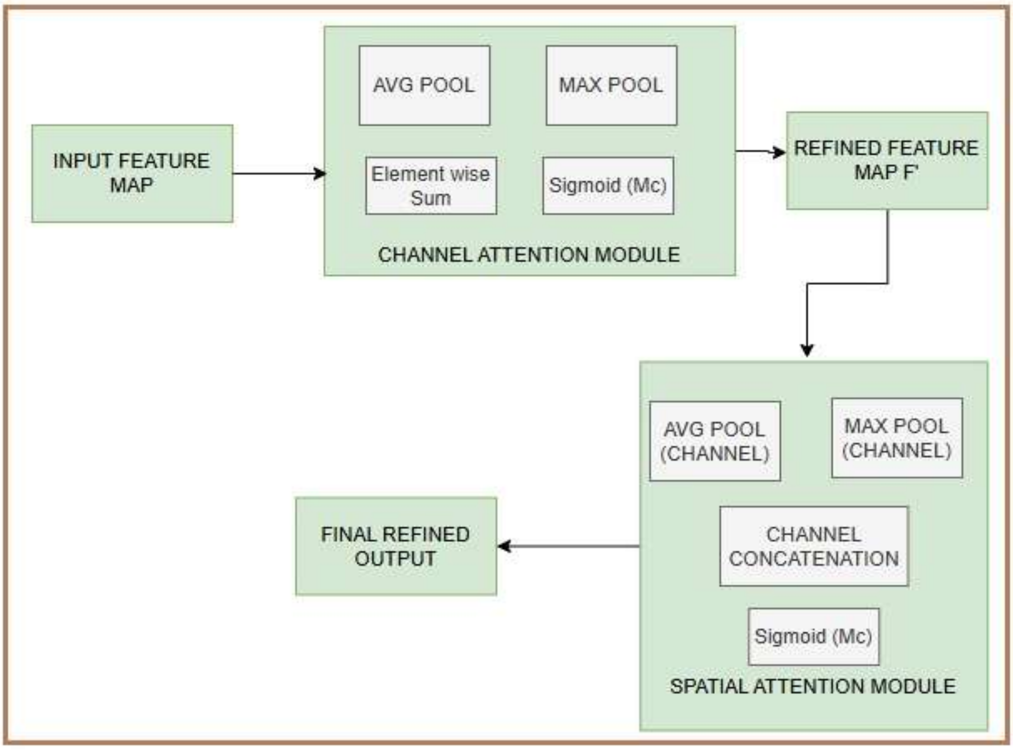


**Figure 2:** CBAM Architecture

The above figure 2 demonstrates the CBAM model architecture. CBAM module upgrades the representation of features by sequential channel and spatial attention. The channel attention module performs global average and max pooling on the features to reduce the spatial dimensions, followed by a common multi-layer perceptron with a single hidden layer to reduce the channels by 16. The weights of channel attention resulting are produced through a sigmoid activation and are multiplied with the input feature map. The spatial attention module then uses channel-wise average and max pooling, concatenates the outputs and uses a 7x7 convolutional layer with sigmoid activation to generate spatial attention weights. These local refinements also highlight informative areas and downplay irrelevant backgrounds to generate polished feature maps to be passed to subsequent processing.

## Result and Discussion

The chapter presents the results of the experiments conducted in accordance with the proposed methodology and the comparison with the previously existing systems. An artificial neural network with transfer learning methods was used to extract features, which were then classified. Experiments were done in Python on the Google Colab platform with the use of a T4 graphics processing unit. The main aim of this study is to evaluate the performance effectiveness of the model developed.

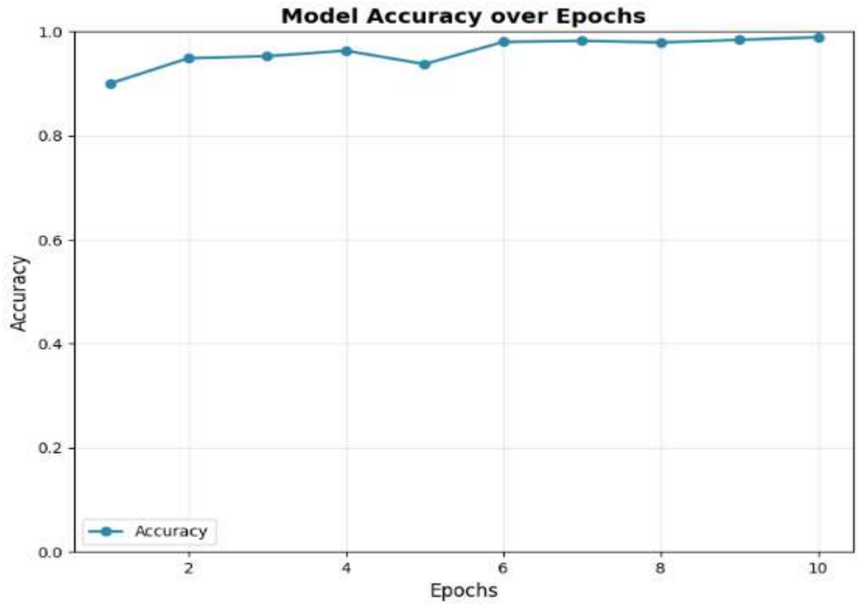


**Figure 3:** Accuracy over epoch graph

The model exhibited a steady improvement in performance throughout ten training epochs in predicting brain tumors as shown in above figure 3. The starting accuracy at epoch one was 90.01 percent with an equal F1-score of 89.90 percent, which reflects a good baseline. The accuracy progressively rose to 96.34 percent by the fourth epoch, but there was a slight variation at the fifth epoch with 93.75 percent accuracy indicating slight overfitting behaviour. The model became extremely stable beginning with epoch six, reached 98.02 percent accuracy and then increased to 98.25 percent, 97.94 percent, 98.40 percent, and eventually, the highest accuracy of 98.93 percent in epoch ten. Precision, recall and F1-scores were consistently consistent with the accuracy values, and there was no bias in performance in any of the classes, making it balanced between all tumor types. The loss of validation was reduced to 0.0397 instead of 0.2619, which proved successful learning. The general findings are that the CBAM-enhanced MobileNetV3 with MLP classifier is a very effective brain tumor classifier with final accuracy of 98.93 percent and it can be a very effective tool in clinically aiding in diagnosis.

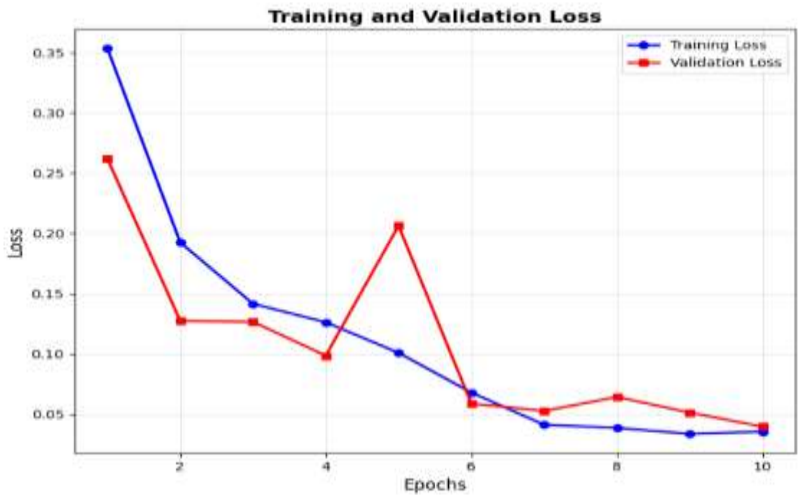


**Figure 4**: Training and Validation loss

The above figure 4 demonstrates the training and validation loss values steadily decreased over ten epochs and it indicates successful model learning without any significant overfitting. The high generalization capability of the brain tumor detecting model in terms of the minimal gap between the two curves of loss shows that the model is reliable when working with unknown data and there is no major difference between the curves.

**Table 01:** Training MLP Classifier Epochwise

| Epoch | Train Loss | Val Loss | Accuracy | Precision | Recall | F1Score |
|---|---|---|---|---|---|---|
| 1/10 | 0.3535 | 0.2619 | 0.9001 | 0.9071 | 0.9001 | 0.8990 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2/10 | 0.1926 | 0.1275 | 0.9489 | 0.9510 | 0.9489 | 0.9490 |
| 3/10 | 0.1416 | 0.1267 | 0.9527 | 0.9560 | 0.9527 | 0.9530 |
| 4/10 | 0.1263 | 0.0985 | 0.9634 | 0.9632 | 0.9634 | 0.9632 |
| 5/10 | 0.1009 | 0.0985 | 0.9375 | 0.9472 | 0.9375 | 0.9376 |
| 6/10 | 0.0680 | 0.0588 | 0.9802 | 0.9801 | 0.9802 | 0.9801 |
| 7/10 | 0.0412 | 0.0527 | 0.9825 | 0.9824 | 0.9825 | 0.9824 |
| 8/10 | 0.0386 | 0.0643 | 0.9794 | 0.9798 | 0.9794 | 0.9794 |
| 9/10 | 0.0337 | 0.0513 | 0.9840 | 0.9844 | 0.9840 | 0.9840 |
| 10/10 | 0.0355 | 0.0397 | 0.9893 | 0.9896 | 0.9893 | 0.9893 |

The MLP classifier was trained to take ten epochs as shown in Table 01 and it was observed that the performance was steadily improving. The training loss dropped from 0.3535 to 0.0355 and the validation loss dropped from 0.2619 to 0.0397, which means that the training was successful with no overfitting. In line with that there was an improvement in accuracy as it grew to 98.93% at the last epoch. The same pattern was observed in precision, recall, and F1-score which at the epoch 10 showed 98.96, 98.93, and 98.93 respectively. In between epochs (e.g., epoch 5), small variations in the validation loss and accuracy were noticed however, they did not impede the overall convergence. These findings show that MLP classifier can produce high reliability and balanced outputs in detecting brain tumors.

Unlike traditional transfer learning methods that do not use selective attention mechanisms to extract features [14][20], the framework proposed uses a Convolutional Block Attention Module (CBAM) before the classification process. This module enhances feature representations by using both channel-wise and spatial attention. In contrast to previous works that utilized single convolutional networks or hybrid network models that achieved only a moderate accuracy [7][11], the present CBAM-improved MobileNetV3 with an MLP classifier achieves an accuracy of 98.93%. This is better than a number of the existing methodologies such as VGG16 with SVM (98.87%) [14] and the POD-CNN model (95.88%) [3]. Moreover, the present model exhibits lower overfitting as compared to the methods that do not employ attention mechanisms [15][18] as the validation loss of 0.0397 is low. MobileNetV3 is used to enhance computational efficiency, hence offering a practical and high-performance solution to clinical brain tumor diagnosis.

**Table 1:** Comparison of existing system with proposed methodology

| **Existing System** | **Proposed System** | **Improvement in Proposed System** |
|---|---|---|
| Uses standard CNNs or pre-trained models (VGG16, ResNet50, InceptionV3) without attention modules for feature extraction [7][12][14] | Integrates CBAM (channel and spatial attention) after MobileNetV3 feature extraction to refine feature maps | Enhances focus on diagnostically relevant regions while suppressing irrelevant features, improving classification accuracy and interpretability |
| Employs classifiers such as standalone SVM, Random Forest, or traditional CNNs without attention-based feature refinement [5][14][18] | Uses an MLP classifier with two hidden layers (512 and 256 neurons), batch normalization, and dropout regularization | Reduces overfitting and improves generalization, achieving balanced precision, recall, and F1-scores (≈98.93%) |
| Achieves moderate accuracy: VGG16+SVM (98.87%) [14], POD-CNN (95.88%) [3], IRNet (99% but without attention) [7] | Achieves 98.93% accuracy with CBAM + MobileNetV3 + MLP, validated on a 4-class MRI dataset (7,000 images) | Provides competitive or superior accuracy with stable learning curves and low validation loss (0.0397), demonstrating reliability |
| Lacks explicit spatial-channel attention, leading to potential misclassification of tumors with irregular morphology [6][8] | Applies sequential channel and spatial attention via CBAM, followed by global average pooling | Extracts more informative features, improving detection of gliomas, meningiomas, and pituitary tumors |
| Some methods use computationally expensive architectures (e.g., 3D U-Net) or lack real-time practicality [1][19] | Employs lightweight MobileNetV3 with attention and MLP, trained on Google Colab (T4 GPU) | Balances high accuracy with computational efficiency, suitable for resource-constrained clinical environments |

## Conclusion

This study was able to create a brain tumor detection model that integrates MobileNetV3 feature extraction with CBAM attention and MLP. The method proposed scored 98.93% accuracy on a four-class MRI dataset of 7,000 images, surpassing the existing methods such as VGG16 with SVM. The CBAM module contributed to the better representation of features, where irrelevant information was suppressed and regions of diagnostic importance were emphasized. Minimal overfitting and good generalization were ensured by low validation loss of 0.0397. This model can provide effective, automated assistance to radiologists, which could decrease the time to diagnosis and positively influence patient outcomes in a clinical setting.

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