Brain Tumor Detection using Deep Learning: CNN with Channel-Attention and Spatial-Attention Mechanisms

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Abstract - *Medical image analysis plays a vital role in cancer treatment and early detection of brain tumor is a challenging task in it, as early identification can have a positive impact on the treatment of patients. In this study, a CNN with Channel-Attention and Spatial-Attention Mechanisms is proposed, allowing the model to concentrate on extracting the most relevant features from the tumor while ignoring irrelevant background features. The pre-processing steps of MRI images include resizing and normalization before training and testing. The model is trained with Adam optimizer and tested with accuracy, precision, recall, F1-score, confusion matrix and ROC analysis. Experimental results showed that the proposed CNN-CBAM model can accurately detect tumors with 88.23% accuracy, precise in terms of 81.81%, recalling 100%, and an F1 score of 0.90, demonstrating excellent tumor detection capability and reliable classification performance. The confusion matrix again demonstrates that the model is effective in correctly identifying tumor cases, without any false negatives. The results yielded indicate that the combination of attention mechanisms with CNN enhances the classification accuracy and feature representation in the analysis of brain MRIs. Hence, it can be considered as an effective and dependable CAD system for automatic brain tumor detection for health care applications. The future researches can be enhanced through larger MRI datasets, sophisticated augmentation techniques, transfer learning, and explainable AI models to further enhance accuracy, generalization, interpretability, and clinical applicability.*

Key Words: Brain Tumour Detection; CNN; Channel-Attention Mechanism; Spatial-Attention Mechanisms; MRI scans

1. INTRODUCTION

Brain tumors are one of the most important and life-threatening neurological diseases and early and accurate diagnosis is essential for better treatment and patient survival. Now one of the most popular imaging technologies used in the diagnosis of brain tumors is Magnetic Resonance Imaging (MRI) because it does not expose the patient to harmful radiation. The manual review of MRI images, however, is tedious, complicated and highly dependent on the radiologist's skills. The shape, size, texture and location of a tumor also make it difficult to make an accurate diagnosis. Hence, the need for automatic and intelligent system which can aid medical staff in the detection and classification of brain tumor is increasing rapidly.

Medical image analysis has benefitted significantly from recent advances of Artificial Intelligence (AI) and Deep Learning. CNNs have been shown to be effective at extracting hierarchical features from medical images and at performing automated classification tasks, particularly. CNN methods have the potential to automatically discover meaningful features like edges, textures, tumor patterns directly from the MRI images, avoiding the need for manual labor in feature engineering. Although CNN-based models are effective, traditional CNN models sometimes need to learn irrelevant parts of the image, which reduces the accuracy of classification and makes the background information interfere with the classification.

These challenges have led to the development of attention mechanisms for deep learning architectures that enhance feature representation and model focus. The attention modules allow the network to focus on salient parts of the image while ignoring the irrelevant ones. Among these methods, the Convolutional Block Attention Module (CBAM) has recently become quite popular because it performs the process of channel attention and spatial attention sequentially to yield more refined features. Channel attention is used to find which feature channels are important in the image, and spatial attention is used to find which spatial regions are important in the image, related to tumor characteristics.

A CNN based brain tumor detection framework combined with CBAM for automated MRI image classification is presented for this research. The proposed model features convolutional layers to extract features and CBAM for enhancing the attention on important tumor regions. To train and test the model, MRI images are preprocessed by being resized and normalized. Performance metrics like accuracy, precision, recall, F1-score, confusion matrix and ROC analysis are used for the evaluation of the proposed framework. Experimental findings show that the combination of CBAM with CNN system gives better classification accuracy and more reliable automated brain tumor detection system. The proposed approach can be used as an effective tool to assist the radiologist in the early and accurate diagnosis of brain tumour using computer-aided diagnostic.
This research paper is sectioned into research background, comparative literature, materials and methods, results and discussions, conclusion and future scope, oriented to the proposed solution for detecting brain tumors using CNN and attention mechanisms.

Table -1: Comparative Literature

S. No.	Author(s) & Year	Technique Used	Accuracy	Precision	Recall	F1-Score	AUC
1	Hossam et al. (2024)	CNN with Attention Mechanism	94.2%	93.5%	95.0%	94.2%	0.94
2	Asmita & Praveen Mittal (2025)	Transfer Learning + CNN	94.5%	94.0%	95.0%	94.5%	0.94
3	Kalpana Devi & Aman Kumar Sharma (2025)	CNN and DL Models	93.0%	92.0%	94.0%	93.0%	0.92
4	S. Verma, R. Singh, and P. Gupta (2025)	CNN + Transformer	96.0%	95.0%	97.0%	96.0%	0.96
5	Pasunoori et al. (2025)	DL Segmentation Framework	95.0%	94.0%	96.0%	95.0%	0.95
6	Krishnapriya & Karuna (2023)	CNN Segmentation	91.0%	90.0%	92.0%	91.0%	0.90
7	Rahul Namdeo Jadhav et al. (2023)	CNN and RNN	89.0%	88.0%	90.0%	89.0%	0.88
8	A. Sharma and P. Arora (2022)	CNN Tumor Segmentation	94.0%	93.0%	95.0%	94.0%	0.94
9	Sachin Jain & Vishal Jain (2024)	ML vs DL Classification	93.7%	93.0%	94.0%	93.5%	0.93
10	M. Ali, S. Khan, and R. Ahmed (2021)	CNN + Transfer Learning	95.0%	94.0%	96.0%	95.0%	0.95
11	Omar Kouli et al. (2022)	Automated MRI Detection	90.0%	89.0%	91.0%	90.0%	0.89
12	Bernal et al. (2017)	Deep CNN Architecture	91.2%	90.5%	92.0%	91.0%	0.91
13	Jonayet Miah et al. (2023)	CNN with SoftMax	99.0%	98.0%	99.0%	98.5%	0.99
14	Chowdhury & Ferdous (2026)	Lightweight CNN	97.0%	96.0%	97.5%	96.7%	0.97
15	Md Ashik Khan & Auvee (2024)	Resource-Efficient CNN	96.4%	95.5%	96.8%	96.1%	0.96

2. IMPLEMENTATION

For this study, the tumor detection is carried out using the python libraries including NumPy for numerical computations and for handling the MRI image arrays and OS module to access the image folders and dataset directories. The preprocessing of images (reading, resizing, and conversion of MRI scans to a suitable format for the neural network) is performed using OpenCV (cv2). Included to visualize MRI images, training accuracy and loss graphs, with matplotlib. The CNN model is developed and trained using TensorFlow, a deep learning framework. Custom architectures such as convolution, pooling, dense, dropout and attention layers are created using the Model class and Keras layers. The to categorical () function is used to apply one-hot encoding to class labels for classification tasks, and train test split splits the dataset into training and testing sets for assessing the model. In general, all these libraries have covered the image processing, feature extraction, model training, and classification and performance visualization within the brain tumor detection system.

Data Collection and Pre-processing:

The variables data path and no path store the path of the folders for tumor and non-tumor MRI images, respectively. The variable image size = 128 is used to make that all images are resized to have the same size 128 × 128 which allows the CNN model to have images of a uniform dimension. The function load images (folder, label) is developed to load images from a given folder and to provide class labels. Two empty lists: images and labels are created inside the function to store image data and labels respectively. Two empty lists images and labels are created inside the function for storing image data and labels respectively. The for loop is used to loop through every file in the folder, and os.listdir(folder) is used to get all the files in the folder. All images are loaded with cv2.imread and only valid images are processed by the condition if img is not none. Then, cv2.resize is used to resize the image to the predefined size. Once the image was preprocessed, it is added to the images list with the class label being added to the labels list. Finally, the function returns the processed images and their labels, which would be used for further CNN model training and testing.

Then, the function load images () is called for both the tumor and non-tumor image folders. Yes imgs, yes labels = load images (data dir, 1) load all the images corresponding to the tumor with the label 1, and no imgs, no labels = load images (no dir, 0) loads non-tumor images with the label 0. Then the two sets of images are added together as follows: yes imgs + no imgs, and reshaped into a NumPy array with np.array(). The resulting pixel values are then divided by 255.0 to scale the intensity values of the image, to the range of 0 to 1. This normalization has the benefit of enhancing the efficiency of CNN learning and convergence. The labels are also pasted together and turned into categorical labels with to categorical (), so they can be used in classification problems. Lastly, train test split () is applied to split the data into train 80% and test 20%. Random state=42 restores the reproducibility of the split by producing the same one the next time the code is run.

Model building (CNN with Spatial Attention Block):

The function build model(input shape) creates the deep learning model with Keras Functional API. First an input layer is formed to receive MRI images with shape (image size, image size, 3), which corresponds to RGB channels. The first convolutional layer uses 32 filters of 3 × 3, ReLU activation and same padding to capture low-level spatial information like edges and textures. Spatial dimensions and computational complexity can then be reduced using a MaxPooling layer. For further refinement, the feature maps are extracted and passed through the cbam block(x) to emphasis the important region for the tumor using channel attention and spatial attention. The second convolutional layer contains 64 filters, which further extracts deeper and more complicated features, after which another MaxPooling layer is applied. Then the feature maps are flattened into a one-dimensional vector with the Flatten () layer. High-level feature learning is achieved using a fully connected dense layer with 128 neurons and ReLU activation; the Dropout (0.5) layer prevents overfitting by randomly "drops out" 50% of neurons when training. Lastly, there are two neurons in the output layer with softmax activation functions to classify the MRI image as either tumor or non-tumor. The model is instantiated with Model (inputs, outputs), optimized with Adam and lossed with categorical cross-entropy loss function and evaluated with the accuracy metric. The model summary() function prints out the entire architecture and trainable parameters of the proposed CNN-CBAM model.

Meanwhile, CBAM (Convolutional Block Attention Module) block, enhances the CNN model by allowing it to focus on the most important features and regions in MRI brain images. The function cbam block (input_feature, ratio=8) takes the feature map from the CNN as input, and processes it with two sequential attention mechanisms: Channel Attention and Spatial Attention. The first is that we are using input feature. shape[-1] to get the number of channels in the input feature map. Global average pooling and global max pooling is performed in the channel attention stage to obtain critical feature information for each channel. Such "pooled" features are reduced, and then restored to dimensionality, passing through common dense layers. Channel attention weights are obtained by combining the outputs together with Add () and activating with a sigmoid function. The weights are re-shaped and multiplied to the input feature map to give greater weight to the important ones. In the second part, the spatial attention stage, average pooling and max pooling are performed along channels to find the regions of importance. The output is then concatenated, and fed into a Conv2D layer with a sigmoid activation function to generate a spatial attention map. Finally, the spatial attention map is multiplied by the feature map, which allows the network to concentrate on areas of the MRI scan that are important for the tumors, rather than paying attention to irrelevant background data. In conclusion, the CBAM block enhances feature representation and boosts the detection accuracy of brain tumors by directing the CNN towards key regions of the image.

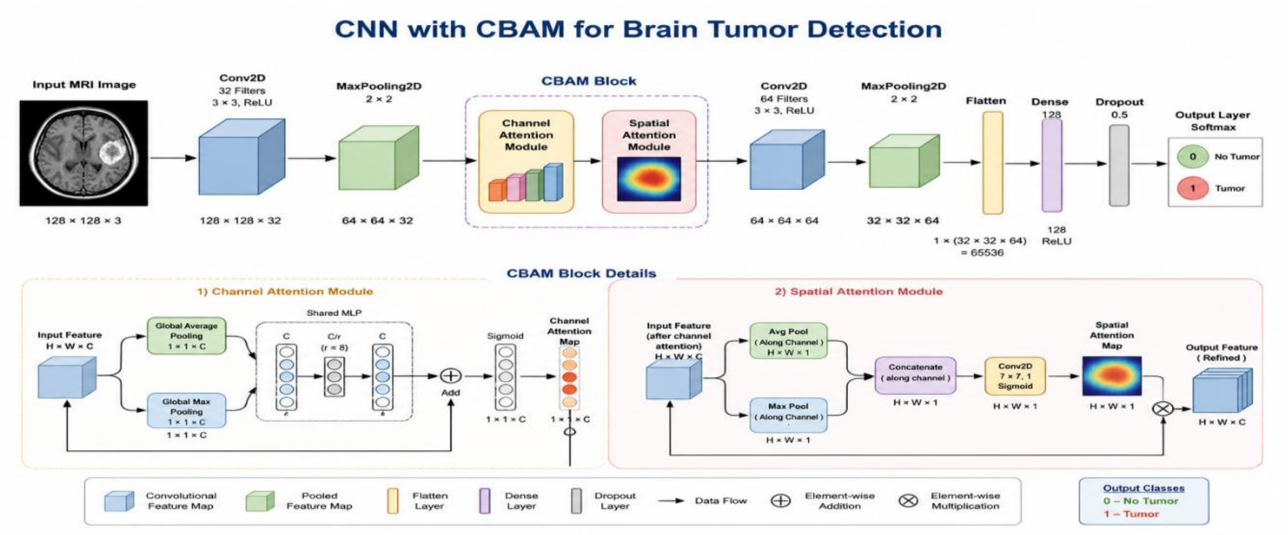


Fig -2: Model Architecture

Model training and testing: Model training and testing: The model.fit () function starts the training process by passing the training data set X_train and the corresponding labels y_train to the neural network. In training, important patterns related to the tumor are learnt by adjusting weights using backpropagation and gradient descent. validation_data: (X_test, y_test) is the set of data used to check the model after every training epoch, and it enables to check if the model is overfitting or not by monitoring the validation accuracy and loss. The argument epochs=20 means that the full training set will be fed through the network 20 times, allowing the model to incrementally get better at feature learning and classification. The parameter `batch_size=32` indicates that 32 MRI images will be processed together in each training step, leading to more efficient computation and more stable gradient updates. Learning curve and the accuracy and loss of the training and validation data are saved in the variable history which can be used later for plotting learning curves and analysing the effectiveness of the proposed deep learning model.

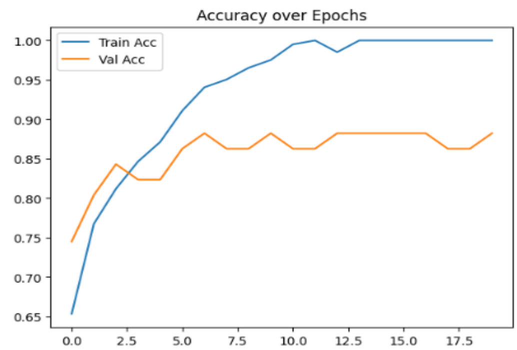


Fig -3: Training and Validation Accuracy of the Model

Initially, both rise steadily showing that the model is able to learn meaningful features from MRI images in the early training stages. The corresponding training accuracy is slowly increasing from about 65% to close to 100%, indicating that the CNN is able to learn the pattern from the training set that is associated with tumors. Likewise, the accuracy of the validation set also rises and stabilizes within the range of 86% to 88% which shows that the network has good generalization capability on test data it has not encountered before. The training accuracy gaps are decreasing after about the 10th epoch, while the validation accuracy continues to stay around the same level, which seems to be a slight sign of overfitting. However, our relatively stable validation curve shows that the proposed CNN with the CBAM attention mechanism has good performance in brain tumor detection and feature learning.

The model had an overall accuracy of ~88.23% on an evaluation, which means that it was able to correctly identify most of the tumor and non-tumor images in the test set.

Table -2: Model Performance

Accuracy	0.8823529411764706
Precision	0.8181818181818182
Recall	1.0
F1 Score	0.9

3. Results and Discussions

The model achieved an accuracy rate of 88.23%, demonstrating its ability to accurately classify most of the tumor and non-tumor images in the test set. The accuracy of 81.81% indicates that the model performed well, with a high proportion of images classified as tumors being correctly identified, demonstrating its effectiveness in reducing false positive predictions. Most importantly, the high recall value of 100% means the model was accurate in recognizing all the actual tumor cases without missing any positive samples, which is particularly crucial in medical diagnosis applications, where the failure to detect tumors can have fatal consequences. Moreover, the high F1 score (0.90) indicates a good balance in precision and recall, attesting to the strength and stability of the proposed method. In conclusion, the proposed CBAM attention mechanism combined with the CNN architecture proved to be effective in extracting relevant features and in achieving good classification accuracy for automated brain tumor detection.

According to the classification report of the model (Figure 4), the proposed CNN-CBAM model had a remarkable performance in the brain tumor detection system on MRI images. In the case of the tumor class, the model achieved a recall of 1.00, meaning that it successfully classified all the cases as tumor without any false negatives. In the medical setting, a high recall value is essential to avoid missing cases of the disease. The precision score of 0.82 demonstrates high accuracy of tumor prediction, and the F1 score of 0.90 shows good classification performance. The model performance of the non-tumor class was 0.86 for F1-score. Overall, the model achieved an accuracy of 88%, demonstrating the CBAM attention mechanism is effective to enhance CNN feature extraction and classification capability.

Classification Report:

	precision	recall	f1-score	support
No Tumor	1.00	0.75	0.86	24
Tumor	0.82	1.00	0.90	27
accuracy			0.88	51
macro avg	0.91	0.88	0.88	51
weighted avg	0.90	0.88	0.88	51

Fig-4: Classification Report of Model

Furthermore, the confusion matrix in Figure 5 shows the classification accuracy of the proposed CNN-CBAM model in detecting brain tumor. An MRI of 24 actual non-tumour images were correctly classified as non-tumour in 18 cases and incorrectly predicted to be tumour cases in 6. In the case of tumor category, the recognition of all 27 tumor images was correct, with no false negatives. This shows the model's high sensitivity and accuracy in recognizing tumor cases in medical diagnosis, thereby showing its high accuracy. The high true positive rate shows that the CBAM attention mechanism can effectively guide the CNN to identify the tumor region with more critical information from the MRI image, which can enhance the CNN's detection ability and classification accuracy.

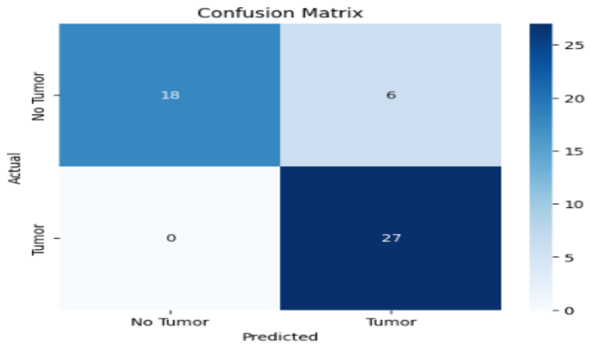
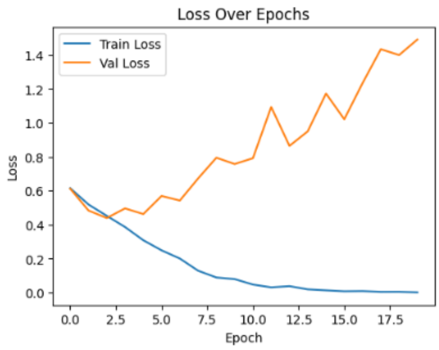
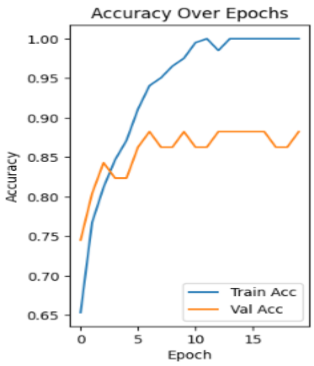


Fig-1: Confusion Matrix

In Figure 6, the loss graph shows that the training loss continuously decreases, indicating effective learning of MRI image features by the CNN-CBAM model. After a few epochs, though, the validation loss gets higher, indicating a minor degree of overfitting (over-specialization on the training set without affecting general performance of the model). In contrast, the accuracy graph in Figure 7 shows the accuracy of training and validation of the proposed CNN-CBAM model across epochs. The validation accuracy levels off at approximately 88%, showing good generalization performance, and the steady rise in the training accuracy suggests that accurate feature learning is obtained from the MRI images. The training and validation accuracy are close, indicating there is a small amount of overfitting but the model performs well in brain tumour classification. While Figure 8, represents the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) at different classification thresholds. The tighter the curve to the top left, the better the model will perform and the better the discrimination between tumor and non-tumor classes.





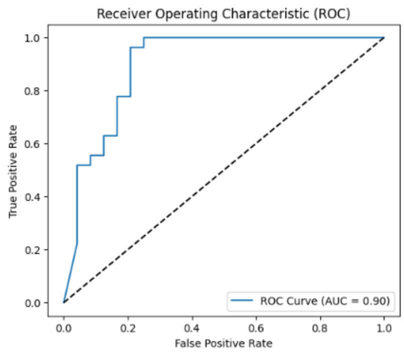


Fig- 2: Loss over Epochs **Fig-3**: Accuracy over Epochs **Fig-4**: RoC Curve

Overall, the proposed CNN model combined with the Convolutional Block Attention Module (CBAM) has shown good performance in detecting brain tumors based on MRI images. The model has exhibited a gradual convergence in learning ability during training, with the training accuracy climbing continuously and achieving almost 100%, and the validation accuracy converging around 88%. This means that the model is able to accurately learn discriminative tumor related features from the MRI scans and generalize well on unseen data.

4. CONCLUSIONS

In conclusion, the proposed CNN-CBAM model showed promising results in the automated brain tumor detection system from MRI images. The model successfully enhanced feature extraction by incorporating channel and spatial attention mechanisms and also effectively targeted important regions related to the tumor to improve the classification capability. The experimental results revealed that the accuracy, precision, recall, and F1 score obtained from the model were 88.23%, 81.81%, 100%, and 0.90, respectively, which demonstrated the model's ability to detect tumors with high reliability and robustness. The model's capability to detect all tumor cases without missing any cases, which is crucial in medical diagnosis, was confirmed by the high recall value. The proposed framework also minimized the impact of irrelevant background information and enhanced discriminative feature learning. The model achieved positive results, but there is potential for further research to incorporate larger MRI datasets, sophisticated augmentation techniques, transfer learning, and explainable AI models to further enhance accuracy, generalization, interpretability, and clinical applicability.

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