Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 3 (2024)

Ensemble XMOB Approach for Brain Tumor Detection Based on Feature Extraction

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Abstract : Brain tumors are a serious health threat in adults. These fast-growing abnormal cell masses disrupt normal brain function. Doctors use various imaging techniques to identify the specific type, size, and location of brain tumors in patients. Accurately identifying and classifying brain tumors is crucial for understanding how they develop and progress. Magnetic Resonance Imaging (MRI), a well-established medical imaging technique, plays a vital role in this process by assisting radiologists in investigating the location of the tumor. Previous models frequently encounter a compromise between accuracy and computational efficiency, lacking an approach that successfully integrates both aspects.This study introduces an innovative ensemble model termed as "XMob Approach" that combines the deep features extraction abilities of Xception with computational efficiency of MobleNet for binary classification of brain Tumor. The Xmob Approach leverages the strengths of both architectures : Xception depthwise seperable convolutions allow for detailed feature extraction whereas MobileNet's lightweight structure ensures efficient computation making it suitable for real life application. This combination aims to enhance in medical diagnostics, promising enhanced accuracy and efficiency. This study explores the potential of integrating these pre-trained architectures to provide real-time, automated diagnostic assistance, improving the speed and precision of brain tumor detection. In our methodology pre-processed MRI scans undergo feature extraction through Xception model, capturing complicated patterns indicative of tumor presence. Simultaneously MobileNet processed these images emphasizing computational efficiency without compromising on performance.The output of both the modesl are then integrated using ensemble technique to improve overall classification accuracy. By integrating the complementary strengths of Xception and MobileNet , the XMob Approach represent a significant step towards the field of medical diagnostic promising improved outcomes for patients through advanced technology.

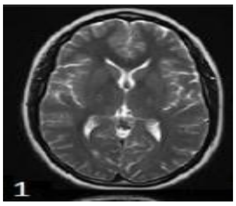
Keyword : Magnetic Resonance Imaging (MRI), Xception, MobileNet, Ensemble Model, XMob

I. Introduction

The brain is one of the most vital organs for human life because of its many roles and functions within the body . In addition to some functions like reasoning, judgment, personality, and memory, it is in charge of managing and organizing each and every organ in the body. As a result, even little issues with the brain have the potential to become serious issues with the entire body[1]. In the US, 24,810 people (14,280 men and 10,530 women) are expected to receive a preliminary diagnosis of a malignant tumor in their brain or spinal cord in 2023(cancer.net). Brain tumors account for 85–90% of primary malignancies of the central nervous system (CNS). In the US, 5,230 children under the age of 20 are predicted to have a CNS tumor diagnosis. Cancer is the uncontrollable development of cancerous cells that spread throughout the body. Cancer can begin from any part of the body. Human cells can grow and multiply to generate new cells as per the requirements of the body. When this procedure breaks abnormal or damaged cells grow and multiply which can be the cause of the tumor[2]. Tumor can be cancerous or non-cancerous. Non-cancerous tumor is known as benign. Cancerous tumors invade nearby tissue and can travel in any part of the body to generate new tumor. A cancerous tumor is known as Malignant. When we remove benign tumor, they do not grow back. Brain tumor starts in the brain which is called primary brain tumor. Sometimes the cancer spreads from the brain throughout the body which can be called a metastatic brain tumor[3]. The size of the brain tumor varies from tiny to very large[4]. In case if brain tumor begins from the part of the brain that is less active, the symptoms of the brain tumor might not be seen right away. This is the reason the brain tumor grows very large before it can be detected[5]. The treatment of the tumor depends upon the size and location of the tumor. Brain tumor can be formed in any part of the brain but in certain areas, a specific type of tumor can be formed[6]. (a) Meninges, the proactive line of the brain where meningioma form (b) Pituitary tumor can be formed in the pituitary gland (c) Medulloblastoma develop from the brainstem or cerebellum (d) Skull base tumor developed on the underside of the brain known as skull base.

Various imaging techniques like X-ray, CT Scan and MRI scans are used by doctors for identifying tumors[7]. The most commonly used MRI scans are T1-weighted and T2-weighted images. By using short Time to Echo (TE) and Repetition Time (TR) T1- weighted images can be produced. T1 attributes of the tissue are responsible for the contrast and brightness of the images[8]. By using longer TE and TR times T2- Weighted scans are produced. Like T1-weighted scans T2 attributes of the tissue are responsible for contrast and brightness.

Artificial intelligence (AI) is one of the most promising approaches to health innovation. Pattern recognition is a method for accurately identifying things from a variety of data sources, such as voice and image, with precise meanings[9]. AI image recognition is made possible by machine learning technology, which reads and processes enormous amounts of scan data for the purpose of learning from it[10]. AI then continuously saves this scan data to improve its accuracy in image identification. The fields of artificial intelligence (AI) and machine learning (ML) have demonstrated potential in creating algorithms that support automatic segmentation and classification using several imaging modalities[11]. To improve diagnosis and therapy, patients with brain tumors need to be accurately classified using the appropriate segmentation technique.



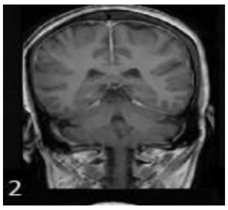


Figure 1: Axial View brain without tumor[8] **Figure 2 : Coronal View brain without Tumor [8]**

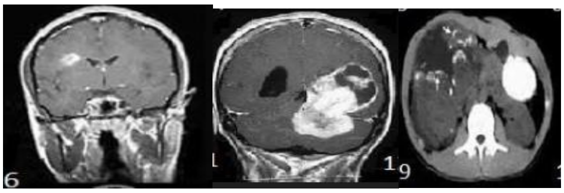


Figure 3 : Coronal View with Tumor[6]

Recent developments in machine learning and deep learning have revolutionized medical diagnostics, particularly in the field of medical imaging. Convolutional Neural Networks (CNNs) have demonstrated notable success in various image classification jobs.

To address these challenges, this study introduces an innovative ensemble model, termed the "XMob Approach," which combines the strengths of two pre-trained architectures: Xception and MobileNet. Xception is known for its deep architecture and efficient use of depthwise separable convolutions, enabling it to capture intricate and complex features in medical images. On the other hand, MobileNet is recognized for its computational efficiency, achieving high accuracy with lower resource requirements, making it suitable for deployment in environments with limited computational resources.

The primary objective of this research is to enhance the accuracy and robustness of brain tumor classification by leveraging the complementary strengths of Xception and MobileNet. The ensemble model aims to diminish the risk of overfitting by balancing the biases and variances inherent in each individual model. Furthermore, data augmentation techniques are applied to increase the size and diversity of the training dataset improving the model's generalization capabilities.

In this study, we preprocess MRI images by resizing them to 256x256 pixels and applying various data augmentation techniques such as rotation, translation, flips, scaling, zooming, and intensity adjustments. The dataset is divided into training, testing, and validation sets to ensure a comprehensive evaluation of the model's performance. Key parameters, including input shape, target size, batch size, learning rate, and the number of epochs, are optimized to achieve the best possible classification accuracy.

This research contributes to the field of medical diagnostics by presenting a robust and high-performing ensemble model capable of accurate brain tumor classification. The findings of this study have significant implications for the timely and precise detection of brain tumors, potentially improving diagnostic outcomes and patient care.

This paper is structured as follows: Section II evaluates prior research in the field of brain tumor detection using deep learning techniques, highlighting key advancements and methodologies. Section III discusses the dataset used in this study, detailing the preprocessing steps and data augmentation techniques applied. Section IV explains the proposed methodology, including the ensemble technique and the integration of Xception and MobileNet. Section V presents the results and discussion, demonstrating the superior performance of the XMob Approach compared to individual models. Finally, Section VI concludes with final remarks and recommendations for future studies, emphasizing the potential of the XMob Approach in providing real-time, automated diagnostic assistance for brain tumor detection.

II Literature Review

The researchers [1] had done Principal Components Analysis (PcA) along with the discrete wavelet transform (DWT), an effective technique for extracting features, were integrated with the classifier, and the evaluation of the performance was fairly good across all performance criteria. The study [2] uses AI algorithms, CNN, and deep learning to improve the accuracy and efficiency of MRI systems in the classification and type-identification of brain tumors. The training was done on brain tumor dataset with the help of pre-trained models : xception,ResNet50, InceptionV3, VGG16 and MobileNet. The percentages of unseen images measured by the F1-scores were 98.50%, 97.50%, 98.00%, 97.25%, and 98.75%, respectively. The early diagnosis of carcinomas before they create physical side effects, such paralysis and other problems, is made possible by these accuracy levels. The goal of the proposed work[3] is to create a deep learning architecture (DLA) that will enable the automatic use of two-dimensional MRI slices for Brain Tumor detection. Applying the deep-features-based SoftMax classifier to pre-trained DLAs, such as AlexNet, VGG16, VGG19, ResNet50, and ResNet101 with the help of SoftMax classifier.

The authors [15] had extracted the features from various Inception modules from Pre-Trained InceptionV3 model and concatenated various features for classification of tumor which were passed to Softmax classifier. Second Pre-trained model DenseNet201 was used for classification which then passed to Softmax Classifier. In both situation accuracy was attained was 99.34% and 99.51% respectively which was considered to be the highest accuracy for brain tumor classification. The researchers [16] had applied CNN model for classification and applied VGG-16 architecture and weights to train the model for binary classification. Feature were extracted from VGG-16 along with other features was provided as input to an Artificial Neural Network classifier through Transfer Learning. The final accuracy was higher then 50% baseline which can be improved by using a various trained images and through hyper parameter tuning which was resulted into 90% accuracy on test data and 86% accuracy on validation set that was fast and accurate in comparison with manual detection.

The authors [17] examine the performance of pre-trained VGG-16, ResNet50 and InceptionV3 model in classification of 253 MR scans The accuracy of VGG-16 with 94.42% was highest. The recall was 83.86%, Precision and F1 Score was 100% and 91.22%. Second model which had given the accuracy was ResNet50 with 82.49%. The researcher [18] had developed the MIDNet-18 CNN architecture that consist of 14 Convolutional Layers, 4 dense Layer 7 Pooling Layers 4 dense layers and one classification. The dataset consist of 2918 images with 1458 images as validation set and 212 images as test set. The MIDNet18 model gained the accuracy of 98.7% which was much higher as compared to VGG16 that obtained the accuracy of 50%. The authors [19] had compared the various deep learning models and observe that deep learning methods had given the better result although due to variable size, appearance, shape and structure accurate detection cannot be predicted and require improvements in the detection.

The researchers [20] applied image edge detection technique to find the region of interest in MRI scans and cropping was done. To increase the size of dataset augmentation was used. Although brain tumor classification require a large amount of dataset but proposed model had worked with small dataset and attained very good accuracy rate as compared to VGG-16, ResNet-50 and Inception-V3 model. The authors concluded that the proposed model require less computational specification with less execution time. Authors [21] had compared various approaches like AlexNet, GoogleNet, ResNet-18 pre-trained models of deep learning classification on MRI images of brain tumor and observed that AlexNet Pre-trained model had given the better result.

Table 1: comparative analysis among brain tumor classification

Year	Proposed Model	Dataset	Measurement
2019[22]	Classifier used Softmax, RBF, Decision Tree, Proposed CNN	1666 training 226 testing	Accuracy attained 98.67%, 97.34%, 94.14% and proposed accuracy 99.12%
2019[23]	LBP + GWT used for feature extraction Feature fusion + KNN as classifier	Local 86 + BRATS 2013 30 + BRATS 2015 273	feature fusion and KNN (K-Nearest Neighbors) shows better performance compared to other classification methods
2019[24]	CNN method for classification by using bilateral filtering	Assembled from UCI Dataset	CNN Proved to better in comparison with Conditional Random Field (CrF), Support Vector Machine (SvM) , Genetic Algorithm (Ga)
2019[25]	Deep Transfer Learning based brain tumor classification	Figshare dataset	Best Classification accuracy compared to related works Good performance with a smaller number of training samples.
2020[26]	Fully Automatic Heterogeneous sgmentation using support vector Machine	CE-MRI Figshare dataset and 3064 T1 –weighted contrast MRI slices	Testing and Training Accuracy 98.51%
2021[27]	Brain Tumor Classification with mean field term within CNN	2065 images from Github	CNN Method is better with 92.7% accuracy in comparison with

	objective function		Conditional Random Field (CRF), Support Vector Machine (SVM) , Genetic Algorithm (GA)
2022[28]	Multi-class classification of brain tumor using Pre-trained DarkNet model	T1W-CE MRI scan 273 (Normal) and 793 (Tumor)	Highest Training Accuracy of 99.60% and testing accuracy 98.54% with sgdm optimizer
2022[29]	23- layers CNN VGG16+23Layers CNN	3064 MRI Images 152 MRI Images	97.8% classification Accuracy 100% classification Accuracy
2022[30]	CNN model consist of 6 layers with 4 Convolutional layers, 1 fully connected and one output/classification layer	3264 MRI images	Classification done successfully and was able to predict MRI scans
2024[31]	Automated segmentation of brain tumor and classification framework	CE-MRI Brain Dataset	Accuracy 98.2% and processing time less 0.42 seconds as compared to existing approaches

Table 1 explain the comparative analysis among brain tumor classification research employs through various techniques with CNN-based methods generally outperforming traditional approaches. Datasets range from local collections to public sources like BRATS and Figshare. Most studies achieve over 98% accuracy with some reaching 100% with certain limitaions of either small dataset or time taken is more. Deep learning, particularly CNNs and transfer learning using pre-trained models like DarkNet and VGG16 shows promising results. Some approaches use feature extraction techniques before classification while others rely on end-to-end deep learning. Ensemble methods and hybrid approaches demonstrate potential for improved performance. Processing time is emphasized in some studies, highlighting the importance of efficiency in clinical applications. Overall, the field is trending towards deep learning methods for their superior accuracy and generalization capabilities.

III Proposed Method :

The current study aims to design an efficient and effective model for medical image analysis for classifying brain tumors. The key research challenge attempted by this ensemble method is the inadequacy of individual model architectures to comprehensively capture the diverse range of characteristics required for precise brain tumor identification in MRI scans. Single-model approaches often fall short in their ability to fully encapsulate the complex and varied features present in brain tumor images possibly leading to incomplete or inaccurate classifications. This limitation highlights the need for a more sophisticated, multi-faceted approach that can effectively synthesize different aspects of tumor morphology and appearance across various MRI modalities. By combining distinct model architectures, each with its own strengths in feature detection, the ensemble method aims to overcome these constraints and provide a more robust and comprehensive analysis of brain tumor MRI data.

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3.1 Pre-Processing : In pre processing MRI images for the use of deep learning model image resizing is required as both the model Xception and MobileNet requires a specific input size of 224 × 224 pixels which ensures that the input dimensions match the model's architecture allowing for effective feature extraction and classification. Once resized the pixel values of the MRI images need to normalized which is achieved by scaling the pixel value to the range [0,1] dividing each pixel value by 255. Normalization helps in stabilizing the training process by ensuring that input values are within a standard range which is essential for the models to converge effectively.

Data augmentation is done for enhancing the model's generalization capabilities. Random rotation, flipping and brightness adjustments introduce variability in the dataset. Augmentation help in creating more robust model which can perform well on unseen data by preventing overfitting to the training set.

MRI images which are single-channel grayscale images, channel adaption is required to fit the models designed for RGB inputs which can be done by replicating a single grayscale channel three times to create a pseudo-RGB image. This adaptation allows the MRI images to be compatible with the pretrained models which are designed to handle three-channel color images.

Intensity standardization is applied to ensure consistent contrast and brightness across all images. This step is essential for enhancing the visibility of relevant features and ensures that model learns from uniformly contrast images that improves overall performance and reliability of the model. By applying these preprocessing steps the MRI images can be effectively prepared for use with ensemble model enabling accurate and efficient medical image analysis.

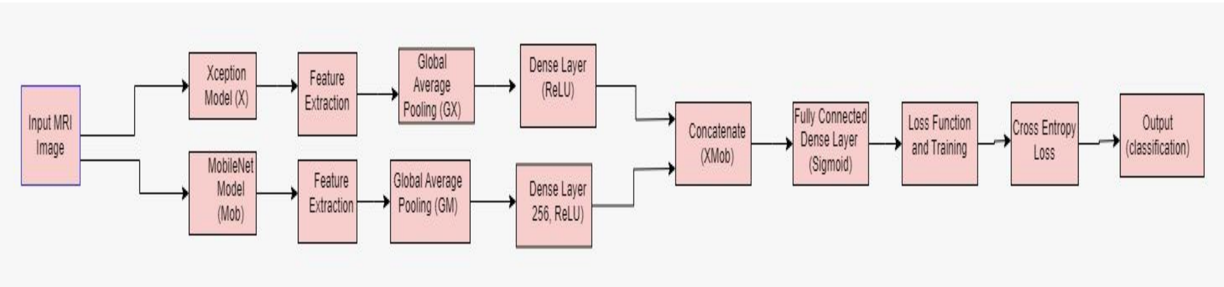

Figure 4 : Structural design of proposed Model (XMob)

3.2 *Ensemble Model :*Ensemble model that combines the strength of Xception and MobileNet pre-trained architectures for brain tumor binary classification is the proposed methodology that exhibits highly effective approach. Xception model is used for its deep architecture and efficient use of depth wise divisible convolutions, excels at capturing complicated features in medical images, making it expert at recognizing delicate patterns that indicates tumors. MobileNet is used for its computational efficiency that achieve higher accuracy with lower resource requirements and is used where computational resources are limited. By combining these two models the ensemble influences their complementary strengths, enhancing feature extraction and improving simplification to new data. Ensemble approach also reduces the risk of overfitting as the ensemble can be able to balance the biases and variance associated with each individual model ,that can lead to more stable and reliable predictions. The variety in their architecture ensures that ensemble can capture both complex and lower level details which help in achieving high accuracy and robustness compared to single models, making it a reliable brain tumor detection and classification and help in improving diagnostic and treatment outcomes.

*3.3 Convolutional Layer :*The common network in ensemble model involves a sequence of convolutional layer followed by ReLU activation function , another convolutional layer, another ReLU activation and then max pooling layer. Four sets of Convolutional (Conv.) and max pooling layer used in the proposed ensemble model. Both Xception and MobileNet Processed the input MRI image independently. Xception provided deep, intricate feature analysis whereas MobileNet offered rapid and efficient feature extraction. The feature map from both network then combined through weighted averaging. This method captured a wider range of tumor characteristics from granular details to broader structural anamolies and at the same time providing a balance between computational depth and speed. The variety in architecture and feature extraction methods help reducing individual model biases and improves the overall generalization capability of the ensemble system.

3.4 *Fully Connected Layer :*Fully connected layers are found at the end of each network which are helpful in interpreting the high level feature extracted by the convolutional and max pooling layers and translating them into final classification decisions.

In Xception , the fully connected layers come after the deep stack of separable convolutions. These layers take the flattened output of the final convolutional layer and progressively reduce its dimensionality mapping mapping it to the output classes representing various types of brain tumors. Xception's fully connected layers force the rich, complex features extracted by its deep architecture to make layered distinctions between tumor types.

MobileNet, designed for efficiency, uses fewer fully connected layers and employs a global average pooling layer followed by a single fully connected layer. This efficient approach aligns with MobileNet's goal of minimizing computational cost while still providing effective classification capabilities.

In the proposed model for brain tumor classification the fully connected layers of both the network serve several functions like feature integration, non-linear transformation, dimensionality reduction, class probability distribution and model specialization. In the ensemble context, the fully connected layers of Xception and MobileNet work complementarily. Xception's more extensive fully connected structure allows for more complex decision-making based on intricate features, while MobileNet's efficient approach provides rapid, high-level classifications.

3.5 Algorithm : Brain Tumor Classification for from MRI scans

Input

- XX : Input image data
- YY :True label for input data
- $\theta X\theta_X$: Parameters for the xception Model
- $\theta M\theta_M$: Parameters for the MobileNet Model
- $\theta D\theta_D$: Parameters for the Dense layer in the ensemble model
- α : Learning Rate
- epochs : Number of Training epochs
- batch_size : Batch size for training

Output

Trained ensemble model parameters $\theta X\theta_X$, $\theta M\theta_M$, $\theta D\theta_D$

Step 1 : Initialize Models and Parameters

- Initialize the Xception model with parameters $\theta X\theta_X$
- Initialize the MobileNet model with parameters $\theta M\theta_M$.
- Initialize the dense layer with parameters $\theta D\theta_D$

Step 2 : Data Preprocessing

- Preprocess input images XX (e.g., normalization, resizing).

Step 3 : Training Loop

For each epoch in the specified range of epochs:

1. Shuffle the training data.
2. Split the training data into batches of size batch_size

For each batch:

- **Forward Pass :**

1. Pass the batch through the Xception model to get features FXFx: $FX = Xception\ (X;\theta X)F_X = Xception(X;\theta_X)$
2. Pass the same batch through the MobileNet model to get feature FM F_M: $FM = MobileNet(X;\theta M = MobileNet(X;\theta_M)$
1. Apply Global Average pooling to the features: $GX = GlobalAveargePooling(FX)G_X = Global\ AveargePooling\ (F_X)GM = GlobalAveargePooling(FM)G_M = Global\ AveargePooling\ (F_M)$
2. Concatenate the pooled features: $G = Concat(GX;GM)G = Concate(G_X,G_M)$
3. Pass the concatenated features through the dense layer: $Z = Dense(G;\theta D)Z = Dense(G;\theta_D)$

- Apply sigmoid activation to acquire the predicted probabilities : $Y_{pred} = sigmoid(Z)Y_{pred} = sigmoid(Z)$

Compute Loss:

- Compute the cross-entropy loss between the predicted probabilities Ypred$Y$pred and the true labels YY : $L = -\sum i = 1NYilog\ \left(Y_{pred}\ i\right)L = -i = 1\sum NYilog(Y_{pred}\ i)$

Backward Pass and Parameter Updates :

- Compute gradients of the loss with repect to the parameters θXθ$_X$,θMθ$_M$ and θDθ$_D$.Update the parameters using gradient descent : $\theta X = \theta X -_{\propto} \partial L\partial\theta X\theta_X = \theta_X - \propto \partial\theta_X\partial L\theta M = \theta M - \propto \partial L\partial\theta M\theta_M = \theta_M - \alpha\partial\theta_M\partial L\ \theta D = \theta D - \propto \partial L\partial\theta D\theta_D =\ \theta_D\alpha\theta_D\partial L$

Step 4 : Evaluation

- After training, evaluate the ensemble model on a validation set to assess performance

Step 5 : Return the trained Model

The trained ensemble model parameters θXθ$_X$, θMθ$_M$, and θDθ$_D$

3.6 Mathematical representation of an Ensemble Model : Xception and MobileNet (XMob)

Combining the strength of both Xception and MobileNet archietures can create a powerful ensemble model for image classification. The detailed mathematical representation is as follows :

1. Individual Models: Xception and MobileNet

First, let's briefly recall the key components of the Xception and MobileNet models.

Xception Model

- **Depthwise Separable Convolutions**: As previously described, Xception uses depthwise separable convolutions which consist of:
- **Depthwise Convolution**: Applies a single convolutional filter per input channel.
- **Pointwise Convolution**: Applies a 1x1 convolution across all channels.

MobileNet Model

- **Depthwise Separable Convolutions**: Similar to Xception but typically more lightweight and efficient.
- **Depthwise Convolution**: Applies convolution independently on each channel.
- **Pointwise Convolution**: Applies a 1x1 convolution across channels.

2. Combining Outputs for the Ensemble

In an ensemble model, we need to combine the outputs of both models effectively. Here are the main steps:

Input Data

Let XX be the input image tensor.

Feature Extraction

- **Xception Output**: Let $FXFX$ be the feature map from the final convolutional layer of Xception. $FX = Xception(X)FX = Xception(X)$

FX=Xception(X) means that input data XXor tensor is fed into Xception model and resulting output is denoted by FX is the output produced by passing XX through the Xception model.

MobileNet Output: Let $FMFM$ be the feature map from the final convolutional layer of MobileNet. $FM = MobileNet(X)FM = MobileNet(X)$

FM = MobileNet(X) means that the input XX is being processed by the MobileNet model, and the result of this processing is FM or FM is the output produced by passing XX through the MobileNet model.

Global Average Pooling

Apply global average pooling to each feature map to a single value by taking the average of all its elements.This operation help in preventing overfitting and reduces the number of parameters in the model.

For Xception: $GX = GlobalAveargePooling(FX)GX = GlobalAveargePooling(FX)$

Above equation indicates that the Global Average Pooling operation is applied to the feature map FX, and the result is GX.

For MobileNet: $GM = GlobalAveargePooling(FM)GM = GlobalAveragePooling(FM)$

Above equation indicates that the Global Average Pooling operation is applied to the feature map FM, and the result is GM.

Concatenation

Concatenate the pooled features from both models: $G = Concat(GX, GM)G = Concat(GX, GM)$

where ConcatConcat denotes the concatenation operation.

Fully Connected Layer

Pass the concatenated features through a fully connected (dense) layer:$Z = Dense(G)Z = Dense(G)$

Sigmoid Activation

Apply sigmoid activation to get the final class probabilities:$Y_{pred} = Sigmoid(Z)Y_{pred} = Sigmoid(Z)$

3. Mathematical Formulation

Let's summarize the mathematical steps involved in the ensemble model:

1. **Extract Features**:

$$FX = Xception(X), FM = MobileNet(X)FX = Xception(X), FM = MobileNet(X) \quad (1)$$

2. **Global Average Pooling**:

$$GX = GlobalAveargePooling(FX), GM = GlobalAveargePooling(FM)GX = GlobalAveargePooling(FX), GM = GlobalAveargePooling(FM) \quad (2)$$

3. **Concatenate Features**:

$$G = Concat(GX, GM)G = Concat(GX, GM) \quad (3)$$

After extracting high-level features using both the Xception and MobileNet models, then Global Average

Pooling is applied to each of their outputs, resulting in GX and GM, respectively. These pooled features are then concatenated to form G, a comprehensive feature vector that combines information from both models.

4. **Fully Connected Layer**:

$$Z = Dense(G)Z = Dense(G) \tag{4}$$

After combining the pooled features from both the Xception and MobileNet models into a single vector G, which feed into comprehensive feature representation into a dense layer which is denoted as Z=Dense(G), learns to interpret the combined features and make final predictions based on the extracted information.

5. **Sigmoid Activation**:

$$Y_{pred} = Sigmoid(Z)Y_{pred} = Sigmoid(Z) \tag{5}$$

After processing the combined feature representation G through a dense layer, resulting in Z then the sigmoid activation function is applied to obtain Ypred. Ypred=Sigmoid(Z)Y_pred = Sigmoid(Z) converts the linear output Z into a probability value between 0 and 1, indicating that the input belongs to the positive class.

4. Loss Function and Training

To train the ensemble model, we define a loss function and optimize it using gradient descent. Common choices for the loss function in classification tasks are cross-entropy loss.

Cross-Entropy Loss

Let YtrueYtrue be the true labels (one-hot encoded) and YpredYpred be the predicted probabilities. The cross-entropy loss LL is given by:

$$L = -\sum i = 1NY_{true}, \log\left(Y_{pred}, i\right)L = -i = 1\sum NY_{true}, ilog\left(Y_{pred}, i\right) \tag{6}$$

where N is the number of classes.

5. Optimization

Use an optimization algorithm Adam to minimize the loss function and update the model parameters.

Iv Result and Discussion

4.1 DATASET : The research paper investigates the performance of Br35H, a novel deep learning architecture, utilizing a dataset comprising 1000 training, 300 validation, and 200 testing images. The architecture is designed to address specific challenges in image recognition tasks, offering promising results in various applications. Through rigorous experimentation and evaluation, the study aims to assess the robustness, generalization capability, and efficiency of Br35H in comparison to existing models. The utilization of a sizable dataset enables comprehensive training, validation, and testing procedures, ensuring a thorough analysis of Br35H's performance across different scenarios. The findings of this research contribute to the advancement of deep learning methodologies and provide valuable insights for further enhancements in image recognition systems.

Table 2 compares the performance of various deep learning models for an image classification task and show the matrices like time taken (in minutes) and accuracy scores for training, validation and testing sets. MobileNet appears to perform best overall, with the highest accuracy scores and shortest time taken. The ensemble model of Xception & MobileNet achieves the highest accuracy across all sets. ResNet50 seems to perform poorest, with the lowest accuracy scores. VGG19 takes the longest time at over 357 minutes.

Table 2: Comparative analysis of various models to exhibit the accuracy score and time taken for execution

	Time taken	Accuracy score		
Model name	**Minutes**	**Training**	**Validation**	**Testing**
CNN	46.728	0.812	0.7367	0.805
VGG19	357.541	0.839	0.8133	0.85
VGG16	100.146	0.852	0.8333	0.87
InceptionV3	56.866	0.917	0.9133	0.9
ResNet50	128.153	0.691	0.6333	0.69
EfficientNetB0	56.261	0.921	0.8833	0.91
DenseNet201	42.994	0.96	0.8467	0.835
Xception	30.026	0.952	0.9567	0.95
MobileNet	24.682	0.967	0.97	0.975
Ensemble model : Xception & MobileNet	46.286	0.981	0.9767	0.98

In brain tumor classification using several CNN models many key parameter influences the performance and efficiency of the model. Various parameter included are training time (in Minutes), accuracy score for training, validation, and testing datasets. Training time is the indication of the computational efficiency of the model, accuracy scores provide a degree of model's performance , training accuracy reflects how well the model learned from the training dataset, validation accuracy indicates how well the model simplify to unseen data during training and testing accuracy indicates exhibiting the model's performance on completely unseen data. It has been observed that simpler models like basic CNN and older architecture like VGG16 and VGG 19 require more training time as compared to more modern and optimized architectures. Models such as Inception V3, EfficientNetB0 and DenseNet201 exhibit a balance between training time and accuracy . The Xception and MobileNet models excel in both training speed and accuracy. The ensemble model which combines the strengths of Xception and MobileNet proves the best overall performance. Ensemble model achieves the highest accuracy across training, validation and testing datasets by maintaining reasonable training time. This specifies that ensemble methods can influence the complementary strength of different architectures to improve classification performance and robustness. Table 3 outlines the key training parameters used for a XMob model related to the image classification These parameters are crucial for optimizing the model's performance and generalization ability. They reflect a balance between thorough training and measures to prevent overfitting due to small batch size.

Training parameters	**Value**
No. of epochs	25
Learning rate	0.0001
Batch size	2
Dropout	0.5

Table 3 : Description of Training Parameters used in Dataset

The table provides key settings required to train a machine learning model for brain tumor classification using MRI. The number of epochs is set to 25 means model will go through the entire training dataset 25 times that helps the model learn and improve the performance. The learning rate is set to 0.0001 means that the model will make very small adjustments to its weights during training. This conservative approach helps ensuring stable and gradual conjunction which reduces the risk of exceeding optimal weights.

The batch size is set to 2 means that the model processes two images at a time before updating its weights. Although the training time may increase, this small batch size can yield a more detailed gradient estimate. A dropout rate 0.5 means that 50% of neurons are randomly deactivated during each update step. This technique has been applied to prevent over drafting ensuring that the model generalizes better to unseen data. Collectively these parameters are crucial in optimizing the training process to enhance the model's ability to accurately classify brain tumors from MRI scans.

For evaluating the performance of various pre-trained models in brain tumor classification provide the comprehensive view of their classification capabilities beyond simple accuracy matrics. A confusion matrix is a 2×2table for binary classification tasks which displays the number of true positive (Correctly identified tumors), true negatives (Correctly identified non-tumor cases), false positives (incorrectly identified tumors) and false negatives (missed tumors).Each of these values offers insights into different aspects of the model's performance.

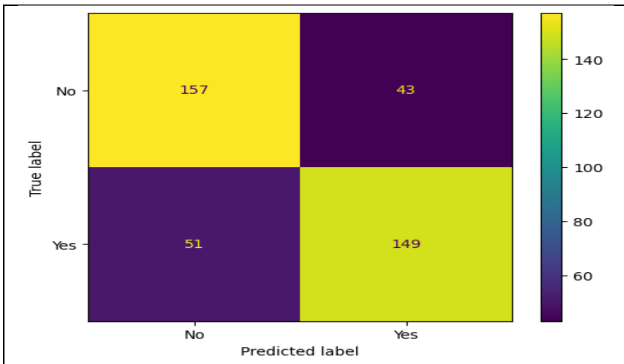

Figure 4 :CNN

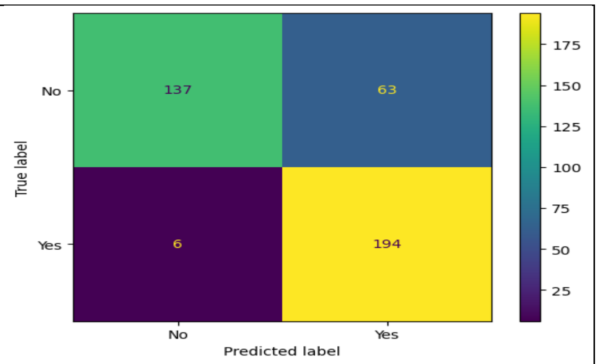

Figure 5 :VGG 19

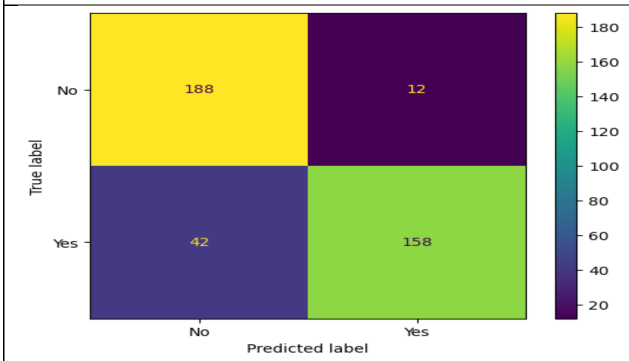

Figure 6 :VGG16

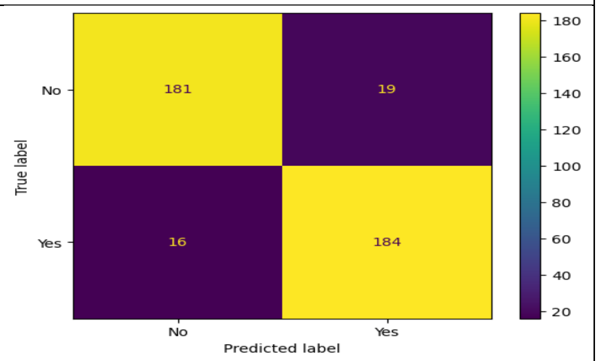

Figure 7 : Inception V3

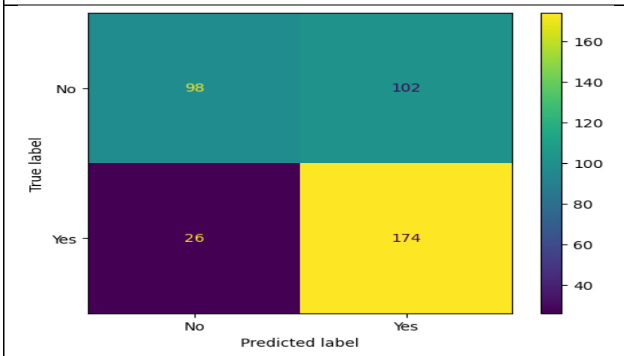

Figure 8 : ResNet50

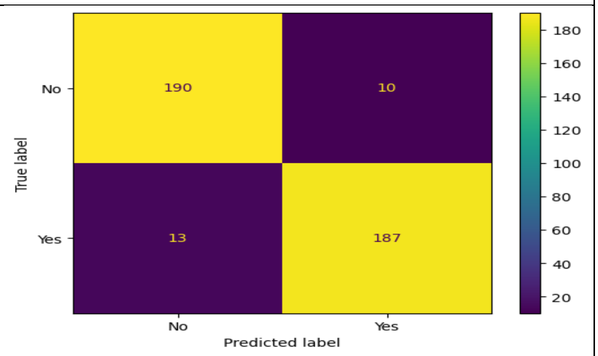

Figure 9 : EfficientNetB0

ISSN: 1001-4055
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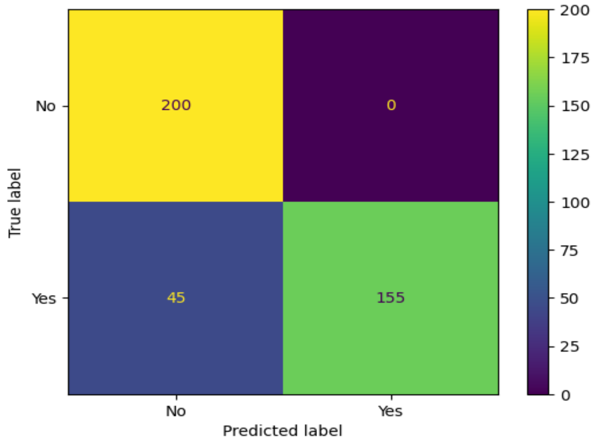

Figure 10 : Dense Net201

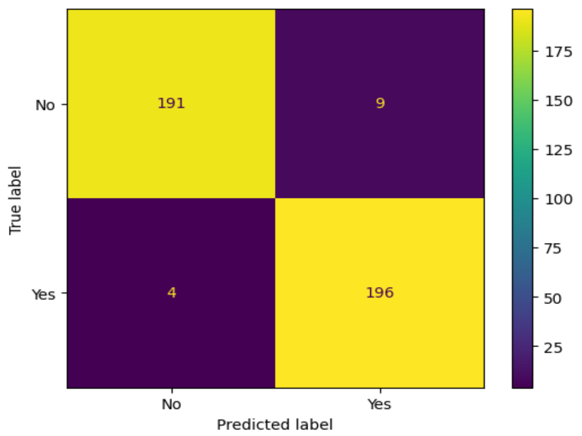

Figure 11 : Xception

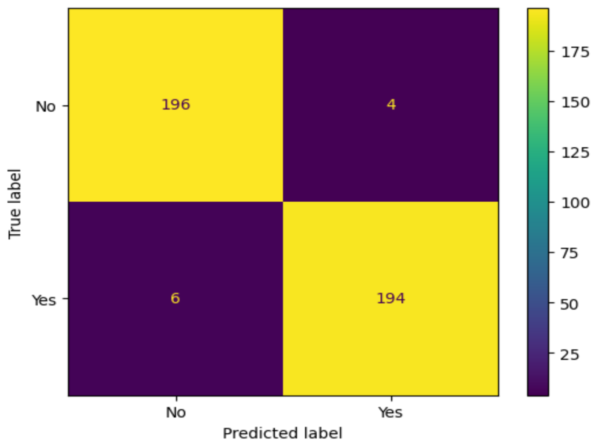

Figure 12 : MobileNet

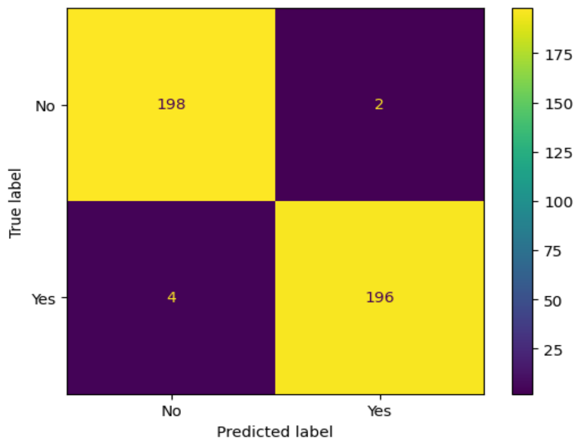

Figure 13 : Ensemble Model

The ensemble model merging Xception and MobileNet show the best performance in the confusion matrix with the highest true positive and true negative counts and the lowest false positive and false negative counts. The reason behind is that ensemble influences the strength of both models, rewarding for their individual weaknesses and providing a more balanced and accurate classification. MobileNet, known for its speed and accuracy validate a strong performance in the confusion matrix, reflecting itsrobust capability in classifying tumorous and non-tumourous.

VI Conclusion

The proposed system employs deep transfer learning to extract features from brain MRI images, achieving high classification accuracy compared to related studies. The XMob ensemble model, combining Xception and MobileNet for brain tumor binary classification, proves superior to individual models. This ensemble leverages the complementary strengths of both architectures: Xception's ability to capture complex, high-level features and MobileNet's efficiency and accuracy. This is evidenced by the highest testing accuracy of 0.98, resulting in improved generalization and reliability that excels beyond each model's independent performance.

XMob balances computational efficiency and predictive power with a reasonable training time of 46.286 minutes, providing a practical solution for clinical applications where both accuracy and speed are critical. The ensemble approach reduces overfitting risk and ensures better handling of variability in brain tumor scans, leading to more reliable and accurate diagnoses.

Overall, XMob represents an advancement in deep learning for medical imaging, offering a highly effective tool for brain tumor detection and classification. While implementing XMob in brain tumor binary classification may be resource-intensive, integrating this model into clinical systems can provide real-time, automated diagnostic assistance to healthcare professionals, enhancing the speed and accuracy of brain tumor detection.

Future research could explore incorporating additional pre-trained models into the ensemble and applying the proposed methodology to multi-class classification problems. Data augmentation techniques and more diverse datasets could further improve model performance. Advanced ensemble techniques such as dynamic ensembling and meta-learning may also enhance XMob's predictive capabilities.

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