Ensemble Deep Learning for Brain Tumor Detection: Integrating InceptionV3 and MobileNetV3 Models on MRI Scans

***Abstract*—Brain tumor detection is crucial for early intervention and treatment. Early detection is critical which considerably enhance patient outcomes. In this study, several deep learning models are utilized for interpreting brain MRI scans and categorizing them into four types: pituitary, meningioma, glioma, and normal. Existing methods also used artificial intelligence (AI) models to detect brain tumors, but these models are prone to error and not reliable. To overcome this, we provide a noble technique that combines two deep learning models. Combining them yields more accurate and trustworthy outcomes than using them independently. The result of our model is measured by accuracy, precision, recall, and F1-score. The results show that the integrated AI strategy outperforms individual models, particularly in accurately distinguishing between various types of brain tumors. Specifically, the combination of InceptionV3 and MobileNetV3 attained an accuracy of 98.20% during training and 98.10% during testing. These findings highlight the potential of sophisticated AI techniques in radiography and the significant improvement in brain tumor identification, which is crucial for clinical use.**

***Index Terms*—Brain Tumor Detection, Deep Learning Models, Ensemble Learning, MRI Scans**

I. Introduction

Since brain tumors can result in serious neurological complications and significantly lower a patient's quality of life, they continue to rank among the most urgent medical issues. Improving treatment results and lowering long-term risks depend heavily on an accurate and prompt diagnosis. But manual MRI scan analysis and other traditional diagnostic procedures are frequently laborious, slow, and prone to human error. For these reasons, automated solutions that can increase reliability, decrease delays, and speed up detection are required.

As a result of their capacity to improve diagnostic precision in medical imaging, machine learning (ML) and deep learning (DL) techniques have become increasingly popular. In the classification of brain tumors, Convolutional Neural Networks (CNNs) in particular have demonstrated excellent performance, particularly when paired with sophisticated feature extraction methods. Despite these developments, there are still obstacles in using deep learning models to their full potential in order to handle the complexity of various tumor features and sizable medical datasets.

In order to enhance brain tumor detection and classification, this study builds on previous research by utilizing CNN-based techniques. The study attempts to provide more reliable diagnostic results and aid in clinical decision-making by examining brain MRI images of both healthy and tumor-affected brains. Furthermore, the study investigates combining attention mechanisms with cutting-edge models like Swin Transformer and EfficientNetV2, both of which have demonstrated promising outcomes in improving classification performance. The ultimate objective is to help create AI-powered diagnostic tools that will improve patient care by detecting brain tumors more quickly, accurately, and automatically. This study aims to:

1) Develop a deep learning framework for tumor detection that improves classification accuracy.
2) Assess neural network performance using models such as InceptionV3 and MobileNet, paying attention to both per-image and per-patient accuracy.
3) Build on lessons learned from prior research while improving classification techniques.

The following is the format of the paper: The existing literature is reviewed in Section 2, the proposed model and its design are explained in Section 3, experimental results are presented in Section 4, findings, limitations, and comparisons with related work are described in Section 5, and concluded in Section 6.

II. Literature Review

Analyzing this study's benefits and limitations is necessary to determine its clinical significance. The use of MRI scans for preoperative planning, which is essential for precise tumor localization and directing surgical procedures, is one of the major contributions. Surgeons can improve patient outcomes and increase precision by optimizing strategies through detailed tumor visualization and characterization. In addition to surgery, MRI-based methods offer a potent non-invasive way to monitor tumor growth and evaluate treatment outcomes over time. To ensure more efficient invention, continuous monitoring is needed [1] [2]

Ensemble deep learning techniques are giving promising results in medical imaging. It generates more reliable and accurate prediction by combining several deep learning models. This method enhances generalizability across different datasets, and it also reduces the possibility of overfitting. It has also been proven that the integration of edge detection with CNN-based architectures can generate high accuracy even on a small dataset. It also shows computational efficiency, making it ideal for practical clinical applications providing faster and more reliable diagnosis [1] [2].

In recent, neural network-based frameworks integrated with ensemble learning were used to classify brain tumors using

MRI scans. By combining the advantages of multiple models, these hybrid models can predict classes more accurately and more efficiently than individual models. Experimental results proved their capability in their speed and accuracy in brain tumor detection, which validate their efficacy. By integrating these methods it creates more reliable AI-driven clinical tools by reducing overfitting and improving classification consistency [2] [3].

The incorporation of ensemble methods into MRI-based workflows highlights their significance in therapeutic applications. In both preoperative planning and treatment outcome monitoring, MRI is still essential for tumor localization and characterization. These procedures are improved by machine learning and deep learning techniques, which increase the efficiency and accuracy of classification. These models, however, are essentially support systems that enhance clinical expertise rather than take its place. In order to ensure that AI-generated outputs meaningfully contribute to decision-making while maintaining patient safety, expert validation is still essential. As a result, MRI imaging in conjunction with ensemble deep learning is a useful development for continuous tumor monitoring and treatment planning [1][3].

The detection and classification of brain tumors has significantly improved thanks to the larger field of deep learning. In automated tumor segmentation and classification tasks, a variety of neural architectures, such as CNNs, ResNet, and DenseNet, have shown promising results, improving diagnostic procedures. Additionally, recent investigations into U-Net variations and transformer-based models have highlighted the potential of sophisticated architectures for dependable performance in clinical settings. Additionally, studies demonstrate the usefulness of colorization techniques for grayscale MRI scans, which improve tissue contrast and facilitate more precise segmentation. When taken as a whole, these developments demonstrate how deep learning is increasingly being used to improve diagnostic precision, effectiveness, and dependability in brain tumor imaging [4][5][6].

III. Methodology

This section provides a brief overview of the proposed method of this study. The Fig. 1 illustrates the methodology diagram.

A. Dataset Acquisition and Preprocessing

The dataset of brain MRI images was gathered from Kaggle [10], which is an open data repository. The dataset contains both healthy and tumor brain MRI images. Dataset classes are shown in Table I. After gathering the dataset several pre-processing and augmentation techniques were applied. Image quality, image size, and shape were determined during this process. After preprocessing, the augmentation process was done carefully. Data augmentation is required for enhancing the generalization of the deep learning models to detect brain tumors. It helps to make the dataset more vast and creates variation. Several augmentation processes shown in Table II, such as rotation, translation, scaling, flipping, and cropping,

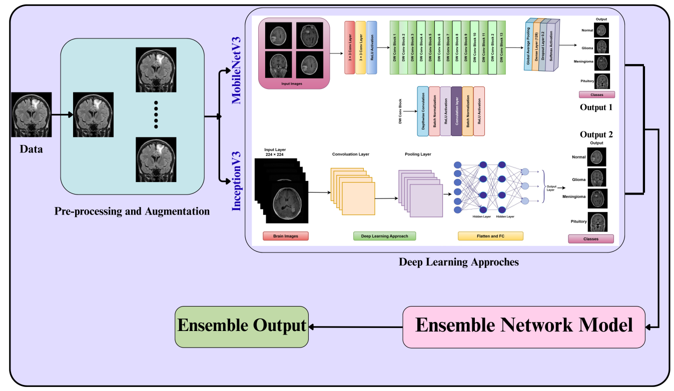

Fig. 1. An overview od the Medthodology Diagram

were done. While translation and scaling take into consideration the spatial shifts and resolution variations present in MRI scans, rotation and flipping replicate various anatomical views. The dataset is further diversified by elastic deformations that replicate pathological brain changes and real-world artifacts [7][8].

To improve the model's overall performance and noise resistance, Gaussian smoothing and intensity adjustment were also employed. These techniques help in standardizing the variance in brain imaging dataset. Using the augmentation techniques dataset was increased to 10,000 samples [9][11].

Other measures were taken to avoid overfitting because of the comparatively small dataset. To make sure the model was consistent across various data subsets, a k-fold cross-validation technique was employed. To keep the model simple, L2 regularization and dropout layers with rates ranging from 0.2 to 0.5 were added. To avoid overfitting issue, early stopping was employed. Early fitting prevent training the model when validation performance reaches its peak.

B. Deep Learning for Imaging of the Brain Tumor

With their superior performance in tasks like segmentation, classification, functional analysis, and biomarker identification, Deep Neural Networks (DNNs) are crucial tools in the analysis of brain imaging. These models are capable of accurately differentiating between healthy and abnormal brains by automatically identifying complex patterns in brain MRI scans. Additionally, DNNs aid in the discovery of biomarkers and patterns of brain activity associated with neurological and psychiatric conditions [13]. Deep learning models improve our knowledge of brain structure and function by using large labeled datasets, which greatly aids in disease management, diagnosis, and treatment plans. They are extremely useful for detecting brain tumors because of their capacity to extract fine-grained features from medical images [12].

Hyperparameter tuning has a significant impact on deep learning models' performance. To increase the model's capacity for generalization, variables such as learning rate, batch size, and regularization strategies need to be optimized. To guarantee peak performance without sacrificing model stability, proper hyperparameter tuning is essential [2]. Due to their demonstrated effectiveness in image classification tasks, InceptionV3 and MobileNet were chosen for this study. These Convolutional Neural Networks (CNNs) are perfect for medical image analysis because they use sophisticated feature extraction techniques. They are also appropriate for use in clinical settings with limited resources due to their effectiveness and lightweight design [13][14].

This study improves tumor classification accuracy by using an ensemble approach that combines InceptionV3 and MobileNet. Different facets of brain tumor characteristics are captured by each model, and overall performance is enhanced by their combination. Compared to using either model alone, this method offers greater accuracy and robustness by enabling a more thorough analysis. These models are excellent for detecting brain tumors because of their complementary nature and effective feature extraction capabilities [14].

C. Hyperparameter tuning and data augmentation

Data augmentation techniques were used to increase the training set size in order to make up for the dataset's limited size, as deep learning models necessitate large datasets. The dataset was expanded to 10,000 images with equal distribution across classes by applying transformations like flipping, rotating, and brightness adjustment. Augmentation improved training efficiency by assisting the model in identifying subtle differences in the 2,870 images that made up the initial dataset.

The dataset was divided into training and testing sets prior to augmentation in order to control data leakage during the process. To ensure that there was no leakage into the test data, transformations were only applied to the training set after splitting. To avoid overfitting to particular patterns, random transformations such as flipping, rotation, and brightness adjustments were employed. Leakage prevention image data generators were utilized, and performance was routinely assessed and leaks were found using a validation set [15][13].

D. Optimization of Hyperparameters

The model's hyperparameters were adjusted systematically using grid search and random search methods. The four main hyperparameters that were optimized include learning rate, batch size, dropout rate, and epoch count. To determine the ideal convergence rate, the learning rate was tested at several values: 10^{-1}, 10^{-2}, 10^{-3}, and 10^{-4}. Different batch sizes (16, 32, 64, and 128) were tested to strike a balance between training speed and model stability. In order to prevent overfitting and preserve model flexibility, dropout rates were tested between 0.2 and 0.5. Early stopping rules were employed to dynamically adjust the epoch count to avoid overfitting and unnecessary computation.

Advanced optimization techniques such as Adam and RMSProp were considered, with Adam being selected due to its fast convergence and flexibility. The InceptionV3 and MobileNet combination weights were optimized for the ensemble model to maximize model cooperation. The selected hyperparameters were validated using cross-validation, which minimized the possibility of overfitting and ensured the model's robustness [16], [8]. InceptionV3 and MobileNetV3's model architecture has been presented in Fig.2 and Fig.3, respectively.

TABLE I
ACTUAL AND AUGMENTED DATASET OF BRAIN TUMOR CLASSES

Classes	**Actual Number of Images**	**Total Number of Augmented Images**
Normal	395	2500
Glioma	826	2500
Meningioma	822	2500
Pituitary	827	2500
Total	2870	10000

TABLE II
DIFFERENT TRAINING OPTIONS AND ITS RELATED PARAMETERS

Training Options	**Reflections/Implications**
Sizes of Image	$227 \times 227 \times 3$
Total Number of Epochs	04
Iterations per Epoch	283
Total Number of Iterations	50
Initial Learning Rate	0.0001
Momentum Rate	0.9
Type of Solver	SGDM
Environment For Execution	Auto
Size of Minibatch	64
Shuffle	Every-epoch
Validation Frequency	1

E. Data Split

After preprocessing and augmentation, the dataset is split into training and validation. 80% of the image in used for training and 20% of the images are used for validation shown in Table III.

TABLE III
DATASET TRAINING AND VALIDATION DISTRIBUTION (80-20 RATIO)

Classes	**Total Images**	**Training (80%)**	**Validation (20%)**
Normal	2500	2000	500
Glioma	2500	2000	500
Meningioma	2500	2000	500
Pituitary	2500	2000	500
Total	10,000	8,000	2,000

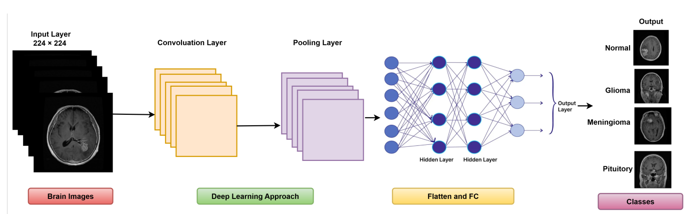

Fig. 2. InceptionV3 Architecture

IV. RESULT ANALYSIS

The model exhibits outstanding accuracy and dependability during both the training and validation stages, according to the

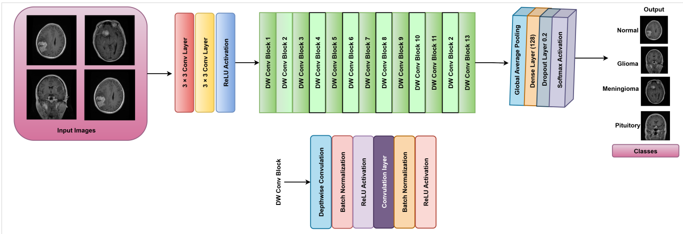

Fig. 3. MobilenetV3 Architecture

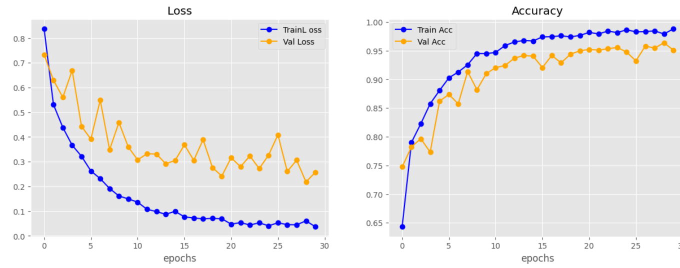

Fig. 5. Accuracy and Loss Curve

performance metrics. The evaluation result has been shown in Fig.4. The model successfully classifies different types of brain tumors, such as normal, glioma, meningioma, and pituitary, with an accuracy range of 94% to 97%. Strong Sensitivity (Recall) is another feature of the model that guarantees accurate identification of positive tumor cases, shown in the confusion matrix of this study in Fig.6. The model's ability to accurately predict the presence of tumors is confirmed by its consistently high precision. The model's overall classification performance is further validated by the F1 Score, which strikes a balance between precision and recall. The model exhibits strong performance with a low False Positive Rate (FPR) and False Negative Rate (FNR), making it a reliable tool for medical diagnostics, despite slight variations between the training and validation phases illustrated in Table IV. In the following Fig.5, the learning curves have been represented, which is evidence of the model's outperformed.

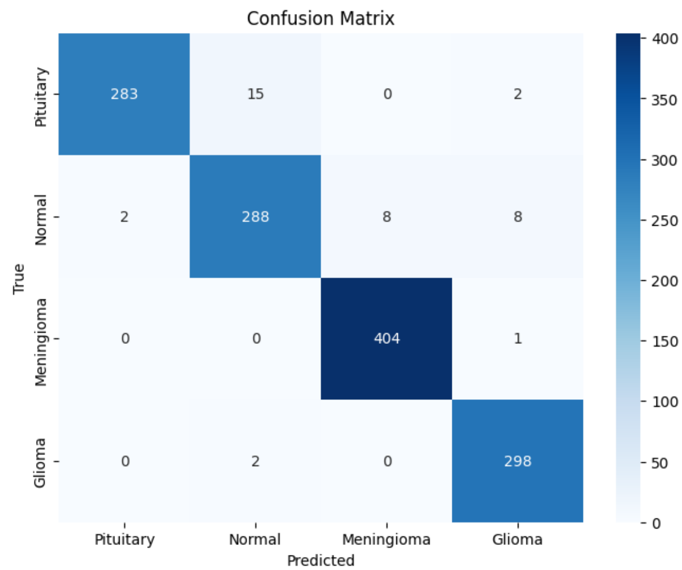

Fig. 6. Confusion Matrix

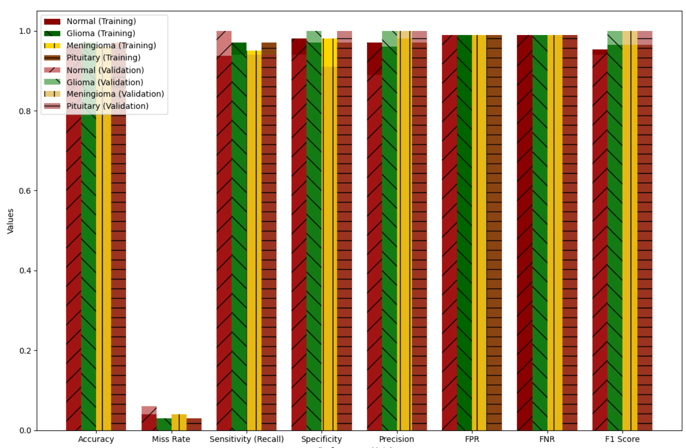

Fig. 4. Evaluation of result

The model's excellent ability to correctly identify different tumor types is demonstrated by the confusion matrix for brain tumor classification. The majority of cases are correctly classified by the model, with pituitary, glioma, and meningioma tumors exhibiting the least amount of misclassification. Sometimes, though, normal brain scans are mistakenly identified as meningioma or glioma tumors. The model maintains high sensitivity and precision despite these small errors, guaranteeing accurate tumor detection. All things considered, the confusion matrix highlights the model's strengths and points out areas that could use improvement, especially when it comes to differentiating between similar tumor types. State-of-the-art analysis has been included in Table V, which represents the comparison of this study with the existing research works.

V. Discussion

The research examined in this paper demonstrates significant progress in the use of deep learning models for brain tumor classification. The accuracy and resilience of these models have been greatly improved by the application of ensemble learning and data augmentation techniques. Notable models with accuracies above 98% include CNNs (VGG16, ResNet-50, InceptionV3) and ensemble configurations (InceptionV3 + Xception). However, a gap in the field is created by the inconsistent use of ensemble models across studies, which limits the ability to generalize findings across various datasets. Even though data augmentation has been used extensively, it can still be improved, especially in how it handles MRI artifacts and the variations present in actual imaging situations.

Moreover, even though ensemble models perform better, their computational efficiency is frequently not thoroughly investigated. More research is still needed to determine the trade-off between controlling the computational cost of these

TABLE IV
PERFORMANCE METRICS FOR BRAIN TUMOR CLASSIFICATION

Phases	Normal (Training)	Glioma (Training)	Meningioma (Training)	Pituitary (Training)	Normal (Validation)	Glioma (Validation)	Meningioma (Validation)	Pituitary (Validation)
Accuracy	0.96	0.97	0.96	0.97	0.94	0.97	0.96	0.97
Miss Rate	0.04	0.03	0.04	0.03	0.06	0.03	0.04	0.03
Sensitivity (Recall)	0.937	0.97	0.95	0.97	1.00	0.94	0.94	0.94
Specificity	0.98	0.97	0.98	0.97	0.94	1.00	0.91	1.00
Precision	0.97	0.96	0.98	0.97	0.89	1.00	1.00	1.00
FPR (False Positive Rate)	0.99	0.99	0.99	0.99	0.99	0.00	0.99	0.00
FNR (False Negative Rate)	0.99	0.99	0.99	0.99	0.00	0.99	0.99	0.99
F1 Score	0.953	0.965	0.965	0.965	0.94	1.00	1.00	1.00

TABLE V
COMPARISON OF BRAIN TUMOR CLASSIFICATION STUDIES

Study No.	Dataset	Data Augmentation	Ensemble Used	Deep Learning Models	Performance Metrics	Key Contributions	Limitations
Study [12]	Private	No	No	AlexNet, GoogLeNet, VGGNet	Accuracy: 96%	Applied data augmentation techniques.	No ensemble model, limited dataset.
Study [17]	Private	No	No	Berkeley wavelet transformation (BWT)	Performance: Not specified	Watermarking technique for feature extraction.	Small dataset, handcrafted features, slow.
Study [18]	Brain tumor dataset	No	No	CNN (VGG16, ResNet-50, InceptionV3)	VGG16: 96%, ResNet-50: 89%, InceptionV3: 75%	CNN-based classification for tumor detection.	No ensemble models, lower accuracy.
Study [19]	Private	No	No	DenseNet	Accuracy: 95%	Deep learning applied for tumor classification.	No data augmentation, lacks ensemble approach.
Study [16]	Brain tumor dataset	Yes	Yes	SCNN, VGG16	Accuracy: 97.77%	Addressed overfitting and dataset imbalance.	Limited comparative analysis.
Study [20]	Brain tumor dataset	No	Yes	Not specified	Accuracy: 98.4%	Applied ensemble learning.	Lack of computational efficiency analysis.
Study [21]	Brain tumor dataset	No	No	SVM, KNN, Decision Tree, Naïve Bayes	SVM: 62%, KNN	DT: 63%, Naïve Bayes: 60%	Classical machine learning approach.
Study [22]	Brain tumor dataset	Yes	Yes	Feature ensemble, stacking ensemble	Feature Ensemble: 97.71%, Stacking: 97.40%	Applied feature ensemble learning.	No real-time efficiency evaluation.
Study [23]	BRATS dataset	No	No	Custom model	Accuracy: 98%	Proposed a new model for tumor classification.	No ensemble learning applied.
Study XL-TL	Brain tumor dataset	Yes	Yes	Ensemble (InceptionV3 + Xception)	Training: 98.3%, Testing: 98.5%	High accuracy, ensemble approach applied.	Computational efficiency not analyzed.

models and attaining high accuracy. Not much research has been done on hybrid approaches, which combine deep learning techniques with more conventional machine learning methods like Support Vector Machines (SVM) and Naïve Bayes. More thorough comparative research may shed light on the best ways to combine these methods for maximum precision and effectiveness, particularly in clinical settings.

In order to improve overall performance, future research should concentrate on improving ensemble models by integrating a range of deep learning architectures, including CNNs, RNNs, and transformers. More generalizable models could be produced by using sophisticated data augmentation techniques, such as Generative Adversarial Networks (GANs), to increase datasets and more accurately replicate real-world imaging variations. Furthermore, for clinical applications, real-time computational efficiency optimization is crucial for minimizing computational costs and guaranteeing quicker diagnoses. To increase the models' resilience across various MRI scan datasets, cross-dataset validation ought to be given top priority. Deep learning models for brain tumor diagnosis may become even more accurate, scalable, and applicable by incorporating AI-based tumor detection into Clinical Decision Support

Systems (CDSS) and investigating transfer learning.

VI. Conclusion

In summary, deep learning models—particularly ensemble approaches—have shown a great deal of promise for improving the precision and resilience of MRI scan-based brain tumor detection. Although a number of models, including CNNs, RNNs, and transformers, have produced impressive outcomes, much more can be done, especially in the areas of computational effectiveness, dataset generalization, and practicality. Generative Adversarial Networks (GANs) and other data augmentation techniques offer a chance to increase training dataset size and enhance model resilience. Future studies ought to concentrate on integrating these models into Clinical Decision Support Systems (CDSS), guaranteeing consistent performance across various datasets, and optimizing them for real-time clinical applications. AI-driven brain tumor detection could revolutionize diagnostic processes with further development, improving patient outcomes and enabling quicker, more precise treatment.

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