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Revolutionizing Brain Tumor Diagnosis: Leveraging Transfer Learning and Deep Neural Networks

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***Abstract*— Early detection of brain tumors helps to save a patient's life to a greater extent. Artificial intelligence-driven deep learning techniques, already achieved remarkable accuracy in diagnosing brain tumors, with a trained large dataset of magnetic resonance imaging (MRI), which is the gold standard for brain tumor diagnosis. However, the complicated structure of the human brain forms significant challenges in this process. This study explores the potential of deep transfer learning architectures to enhance the precision of brain tumor diagnosis. The advanced transfer learning architectures such as MobileNetv3, DenseNet169, VGG19, and ResNet152—were meticulously evaluated using a Kaggle dataset, employing five-fold cross-validation for robust results. To address dataset imbalances, image enhancement techniques were applied, ensuring equal representation across four categories: pituitary tumors, normal scans, meningiomas, and gliomas. Among the models, DenseNet169 arose as the top performer, achieving an impressive accuracy of 99.75%, beating the others. These findings give priority of the groundbreaking potential of deep transfer learning in revolutionizing brain tumor diagnosis, offering hope for more accurate and efficient medical imaging solutions.**

***Keywords—Deep learning, VGG19, MobileNetV3, brain tumor,* DenseNet169.**

I. INTRODUCTION

The human brain is located in the skull, and it is a very important organ in performing a variety of functions. There are billions of neurons forming a network that exerts chemical and electrical impulses to direct our existence and experiences [1]. This amazing organ truly serves as the powerhouse of perception, feeling, and personality. The brain epitomizes complexity, as it comprises distinct regions, each with specialized roles. A complex outer layer called the cerebral cortex controls consciousness, and the cerebellum controls balance and coordination [2]. The smooth coordination of our everyday tasks and reactions to outside stimuli depends on these brain regions interacting harmoniously. Despite its resilience, the brain is not immune to threats. A neoplasm or tumor is a mass of tissue formed as a result of abnormal cell division or proliferation [3]. It can occur in any organ, including the brain. Tumors are further divided into two: benign and malignant. A benign tumor is a slow-growing tumor that usually confines itself to a specific area and has less potential to harm. However, they can be dangerous if they happen to press on vital organs or tissues 4. Malignant tumors, on the other hand, are aggressive., capable of invading nearby tissues and spreading through metastasis. Understanding their progression is essential for timely intervention and preserving the brain's intricate functions, which underpin human cognition and experience [5]. An aberrant group of cells inside the brain is called a brain tumor. These tumors can develop from the brain tissue itself or spread to the brain from other parts of the body. [6]. Diagnosing brain tumors necessitates a comprehensive assessment, often involving imaging tests and biopsies to determine the tumor's characteristics and classification. The diverse array of brain tumors stems from different cell types, each presenting unique diagnostic, treatment, and prognostic challenges [7]. Malignant gliomas, arising from the glial cells of the brain and developing in any region, are one such indication of the urgency for effective treatment of aggressive tumor types by means of targeted therapeutic strategies through their complex cellular environment [8]. Meningiomas represent a different class of tumors, which arise from the meninges or the protective membranes surrounding the brain and spinal cord. Importantly, most meningiomas are benign and do not pose an immediate health risk [9]. Tumors may also develop at the base of the brain in the pituitary gland, which disrupts the regulation of hormones, or from Schwann cells, which give rise to the myelin sheath that covers nerve fibers and results in schwannomas [10]. Most problematic and malignant of the brain tumors are glioblastomas, which pose severe problems in both diagnosis and treatment. Gaining insight into the many types of brain tumors will better help in formulating appropriate treatment methods and increase our understanding of brain pathology. [11]. Deep learning and AI have transformed medical imaging, enhancing the diagnosis and treatment of various cancers, including brain tumors. Transfer learning (TL) enables the efficient use of pre-trained models, reducing computational demands and improving accuracy in medical image analysis. Techniques such as VGG19, ResNet152, DenseNet169, and MobileNetv3 excel in identifying patterns in MRI images, achieving high precision in tumor classification. This study proposes a framework utilizing AlexNet, GoogLeNet, and VGGNet, achieving up to 98.69% accuracy in brain MRI classification through fine-tuning and data augmentation. Additionally, a PNN classifier demonstrated robust performance, attaining 83.3% accuracy on MRI images.

II. LITERATURE REVIEW

Various deep learning-based methods have been proposed for brain tumor classification based on MRI images. Transfer learning and CNN-based works in [13][14][15][16] reported significant improvements in accuracy. The performances of some of the state-of-the-art methods are depicted in Figure 12,

showing that models from [13] achieved an accuracy of 83.3%, while state-of-the-art methods from [14], [15], and [16] reached 99.12%, 98.91%, and 98.73%, respectively. Despite this fact, our model has outperformed with an accuracy of 99.75%. It gains an edge over DenseNet169 due to dense connectivity that allows increased feature extraction with improved gradient flow. In comparison with previous works, our approach is much better in generalization with higher classification accuracy; thus, it can be one of the finest candidates to deploy into real medical life.

III. Methodology

A. Dataset

The brain tumor dataset is implemented for model training collected from Kaggle [12]. This dataset includes MRI images of 7,023 patients' brains, both those with and without brain tumors. It includes cases of non-tumor, pituitary gland tumors, gliomas, and meningiomas. This collection includes over 1,600 excellent images in each category. The distribution of images in the training and test sets is broken down in Table 1.

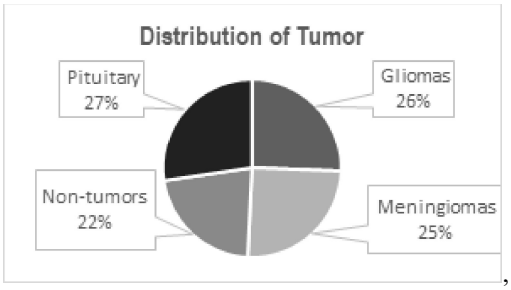

Fig. 1. The Percentage of each type of brain tumor imaging

Fig. 1 [17] shows that the No Tumor class has about 22% images, the Pituitary class has 27% of images, the Glioma class has 26% of images, and the Meningioma class has 25% of images.

TABLE I. Training and Testing Dataset for Each Class

	Training	Testing
Gliomas	1321	300
Meningiomas	1339	306
Non-tumors	1595	405
Pituitary	1457	300

Data is split 80:20 [Fig 2] for training and testing to evaluate model performance and generalizability. Image augmentation, using techniques like rotation, zooming, and flipping, enhances dataset diversity, enabling the model to adapt better to new data. This approach ensures a robust, reliable deep-learning model suited for medical applications with limited data availability. Image augmentation creates a diverse training dataset, improving the model's ability to generalize across various scenarios. By presenting varied examples, it enhances the learning of complex patterns and reduces overfitting. Fig.2 shows normal and augmented brain MRI images.

B. Transfer Learning Model Evaluation

Transfer learning minimizes the time and resources needed for model development by using a previously trained model from one task to solve a related task. For complicated tasks like image recognition and natural language processing, this method works especially well because it allows researchers to refine previously trained models by applying insights from sizable datasets. When training data is scarce, transfer learning performs better than training from scratch, which requires a lot of resources. This study uses four transfer learning models with uniform input sizes of 224 × 224 RGB images, which are widely used in speech recognition, image classification, and medical diagnosis.

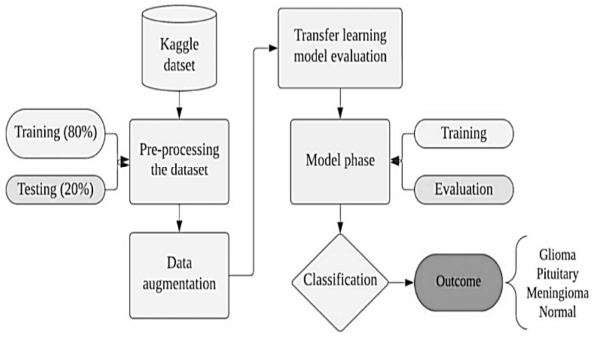

Fig. 2. Proposed Model Architecture

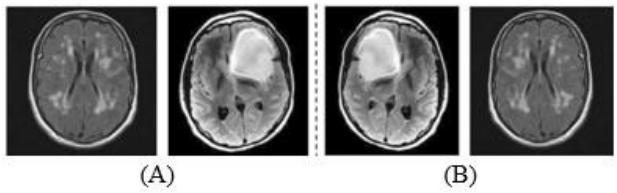

Fig. 3. Augmentation (**A**) normal; (**B**) augmented images.

C. Visual Geometry Group 19(VGG19)

The VGG19 architecture is the evolved version of VGG16, comprising 19 layers in total-16 convolutional and 3 fully connected. In this architecture, feature extraction has been done by using 3x3 convolution filters and max-pooling layers that reduce the spatial dimensions, enhancing its computational efficiency factor [13]. VGG19 uses the ReLU activation function for non-linearity and is very popular in image classification problems. Though popular, more advanced architectures like ResNet and Inception have gained a performance edge over it.

D. Densely Connected Convolutional Networks 169 (DenseNet169)

DenseNet169 is a CNN designed to improve gradient flow and feature reuse by densely connecting every layer to all preceding layers. With 169 layers, it incorporates bottleneck layers with 1×1 convolutions to reduce computational complexity. Dense blocks enhance feature extraction, while transition layers control spatial dimensions. Global average pooling reduces parameters and improves generalization. Known for its parameter efficiency, DenseNet169 achieves competitive accuracy with fewer parameters, excelling in image classification tasks.

E. MobilNetV3

A neural network with an emphasis on accuracy, speed, and efficiency, MobileNetV3 was created for mobile and edge devices. It optimizes computation and memory usage with resource-efficient building blocks and lightweight inverted residuals. With two versions—MobileNetV3-Large for moderate resources and MobileNetV3-Small for highly constrained environments—it successfully strikes a balance between computational overhead and performance. Result

F. Preparation and evaluation of experiments

A sizable image dataset was used in this experiment, and stability was ensured by training in an Anaconda environment. The dataset, which Kaggle maintained, was the same for both training and testing all models. The training set was used to train the Transfer Learning (TL) model, and the test set was used to assess it. Details of the hyperparameters are displayed in Table 2. During training, the cross-entropy loss was applied to both the train and test sets for each epoch. Each model was trained for 50 epochs using the Adam optimizer with a learning rate of 0.001. Training and validation losses for ResNet152, VGG19, and MobileNetv3 were similar, though MobileNetv3 showed signs of overfitting with increasing validation loss. DenseNet169 displayed a stable training process. At the final epoch, MobileNetv3 had a validation loss of 0.5 and training loss of 0.0451, while VGG19 and ResNet152 had training losses of 0.001 and 0.015, with validation losses of 0.1862 and 0.010, respectively. DenseNet169 reached a peak validation accuracy of 99.47% but showed an unusually high validation loss (2454) at epoch 6.

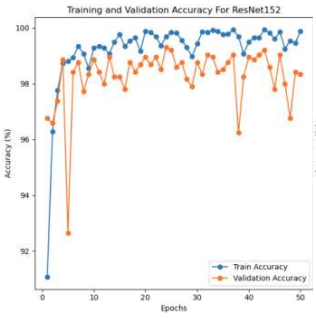

Fig.4. ResNet152

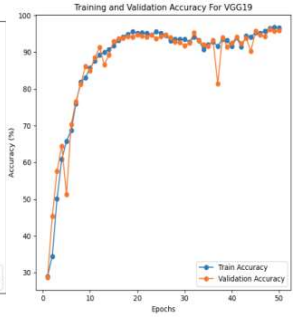

Fig.5. VGG19

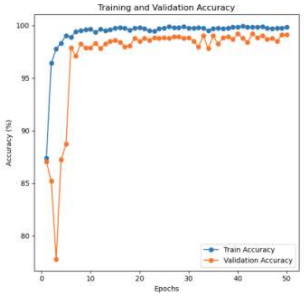

Fig.6. MobilNetV3

Fig.7. DenseNet169

Among the models evaluated, DenseNet169 had the lowest validation loss of 0.051 and it remains the most consistence, achieving 99.22% training and 98.32% validation accuracy. VGG19 and MobileNetv3 also performed well, with VGG19 achieving 99.07% training and 96.72% validation accuracy, and MobileNetv3 reaching 99.75% training and 98.52% validation accuracy. MobileNetv3's validation accuracy fluctuated, while VGG19's accuracies were more stable.

TABLE II: PERFORMANCE OF FOUR TRANSFER LEARNING MODELS OVER 50 EPOCHS

Architecture	Training		Testing	
	Acc(%)	Loss	Acc(%)	Loss
ResNet152	98.86	0.0036	96.92	0.1853
VGG19	99.07	0.0452	95.63	0.1245
DenseNet169	99.75	0.0240	98.52	0.948
MobileNetv3	99.22	0.0360	97.53	0.1172

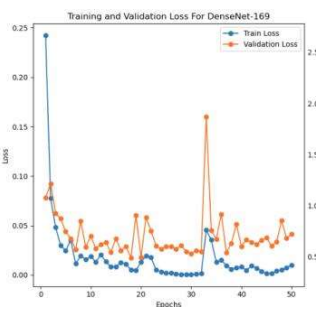

Fig.8 ResNet152

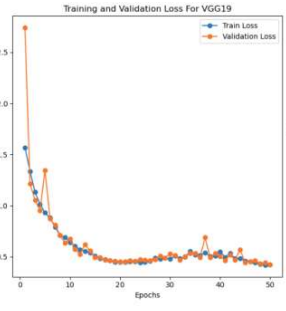

Fig.9 VGG19

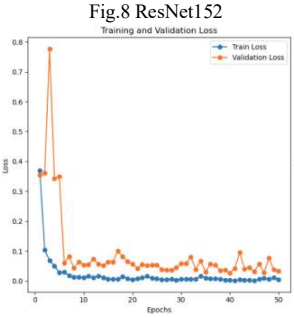

Fig.10 MobilNetV3

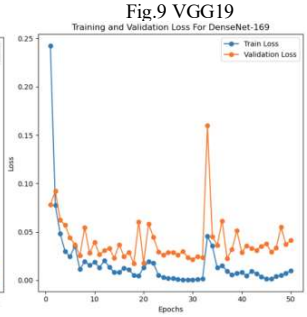

Fig.11 DenseNet169

The accuracy and loss values for all four models are shown in Fig. 4, 5, 6 and 7 sequentially. Table II also shows the summary of the results.

G. Discussion:

This research carefully analyzed model performance with different metrics, focusing on the DenseNet169 confusion matrix, which gives a detailed overview of the classification accuracy of different tumor types. Tumor classes were labeled with numerical values: 0 for "Pituitary," 1 for "Normal," 2 for "Meningioma," and 3 for "Glioma." DenseNet169 performed impressively, classifying 32 'Glioma', 24 'Pituitary', 24 'Normal', and 43 'Meningioma' images correctly. This confusion matrix shows the strengths and weaknesses of the model with respect to the classification of the classes in the tumor. Performance analysis of deep learning models, such as ResNet152, VGG19, MobileNetV3, and DenseNet169, for brain tumor classification using MRI images. Figures 8, 9, 10, and 11 demonstrate the accuracy curves regarding training and validation for each model. These give a view of learning behavior, generalization ability, and overall stability for each model. The performance of four transfer learning models, ResNet152, VGG19, MobileNetV3, and DenseNet169, is evaluated over 50 epochs. In this regard, it is shown in Table II that DenseNet169 has the best balance of high accuracy (98.52%) with a low loss of 0.0958 on the testing set. It is the most effective model for brain tumor classification. Then comes ResNet152 and VGG19 with their respective accuracies at 96.92% and 95.62% in testing, respectively. On the contrary, ResNet152 exhibits higher testing losses at 0.1854, possibly due to overfitting. MobileNetV3 has the

highest testing accuracy, 97.53%, while it has slightly higher training loss, 0.0359, which suggests there is a trade-off between efficiency and generalization. Generally speaking, DenseNet169 has the best performance, with good generalization and minor overfitting. The final model adopted will, after all, depend greatly upon application requirements through the balance of accuracy, stability, and computational efficiency. DenseNet introduces dense connections, linking each layer to every other layer in a feed-forward manner. Contrasting with the traditional CNN, which has L connections for L layers, DenseNet has L(L+1)/2 direct connections, improving gradient flow, feature reusing, and efficiency. This design really cuts down on parameters while improving accuracy. On CIFAR-10, CIFAR-100, SVHN, and ImageNet, DenseNet considerably outperforms the state-of-the-art results but at much lower computational costs[18].

TABLE III. FIVE-FOLD TEST PERFORMANCE OF FOUR TRANSFER LEARNING MODELS ON THE DATASET

Architecture	Class	Precision	Recall	F1-Score	Acc.
ResNet152	Pituitary	0.99	0.93	0.98	0.985
	Normal	0.94	1	0.97	
	Meningioma	0.85	1	1	
	Glioma	0.96	1	0.99	
VGG19	Pituitary	.97	0.93	0.98	0.985
	Normal	0.98	1	0.97	
	Meningioma	0.96	1	1	
	Glioma	0.96	1	0.99	
DenseNet	Pituitary	1	0.85	0.94	0.967
	Normal	0.88	1	0.93	
	Meningioma	0.95	1	0.98	
	Glioma	0.97	1	1	
MobileNetv3	Pituitary	0.99	1	0.97	0.960
	Normal	1	0.83	0.92	
	Meningioma	0.96	1	1	
	Glioma	0.88	1	0.92	

Fig. 12 demonstrates that the proposed model outperformed other models with an accuracy of 99.75%.

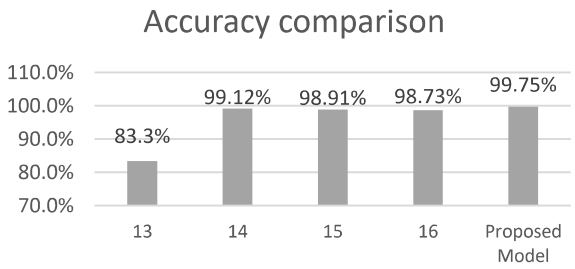

Fig. 12. Accuracy comparison[13][14][15][16] of proposed and state-of-the-art methods.

IV. CONCLUSIONS

Transfer learning models, in particular DenseNet169, were employed in the research presented here for the classification of brain tumors from MRI scans with impressive accuracy of 99.75%. The performance of DenseNet169 was better as compared to ResNet152, VGG19, and MobileNetV3 in terms of recall, accuracy, and precision. Limitations include using a secondary dataset and not considering the real-world scenario in any of the evaluations. In future work, the model will be extended to other imaging modalities such as CT, PET, and ultrasound, overcoming dataset bias and improving generalization. DenseNet169 has great potential for clinical applications, setting a new benchmark in medical imaging and contributing to AI-driven diagnostics that could enable early detection, treatment planning, and improved patient outcomes.

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