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ALZHEIMER BRAIN TUMOR DETECTION USING TRANSFER LEARNING MODEL

Mrs. G. Vijayalaxmi[1*], K. Akshitha[2], M. Vishnu Vardhan reddy[2], K. Ruchitha[2], guguloth Jithender[2]

[1,2]Department of Computer Science and Engineering (AI&ML), Vaagdevi College of Engineering, Bollikunta, Warangal, Telangana.

*Corresponding Email: vijaya_gopu@vaagdevi.edu.in

ABSTRACT

In recent years, the application of artificial intelligence in the field of medical diagnostics has seen significant advancements, particularly in the early detection of neurological disorders. This study focuses on the development of an efficient deep learning-based model for the dual detection of Alzheimer's Disease and Brain Tumors using transfer learning techniques. The early and accurate diagnosis of these conditions is critical, as both can have severe cognitive and physiological consequences if not treated promptly. The existing system employs the VGG16 convolutional neural network architecture, which has demonstrated promising results in image classification tasks. However, due to its relatively shallower depth and limitations in capturing complex spatial hierarchies, the accuracy and generalization performance of VGG16 can be suboptimal for medical image analysis where subtle differences are crucial. To address this limitation, the proposed system introduces VGG19, a deeper variant of the VGG architecture, which enhances feature extraction through its increased depth and improved representational power. By leveraging transfer learning, the pre-trained weights of VGG19 on the ImageNet dataset are fine-tuned on a curated medical imaging dataset comprising MRI scans for Alzheimer's detection and CT/MRI scans for brain tumor classification. Comprehensive preprocessing techniques, including image normalization, augmentation, and resizing, are employed to optimize the input data quality. The model is trained and validated using stratified data to ensure balanced learning. Performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are computed to evaluate and compare the effectiveness of VGG16 and VGG19. The experimental results reveal that the proposed VGG19-based transfer learning model significantly outperforms the VGG16-based approach in terms of diagnostic accuracy and robustness, demonstrating its potential as a reliable clinical decision support system. This research underlines the effectiveness of deep transfer learning models in the domain of medical imaging and contributes to the ongoing efforts in automating neurological disorder detection for faster and more accurate diagnosis.

Keywords: Medical Imaging, MRI Scans, Healthcare AI, Neuroimaging, Diagnosis Automation, Transfer Learning

1. INTRODUCTION

Medical imaging has revolutionized diagnostic practices in modern healthcare, providing a non-invasive means to detect and monitor critical conditions such as Alzheimer's disease and brain tumors. Both of these neurological disorders pose serious risks to human health, affecting cognitive function and overall quality of life. Early detection is crucial for timely intervention and treatment planning. In recent years, deep learning has emerged as a powerful tool in the field of medical image analysis, particularly through the use of transfer learning, where knowledge from pre-trained models is leveraged for specific tasks. The project explores the use of convolutional neural networks (CNNs),

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specifically **VGG16** as the existing model and **VGG19** as the proposed improved model, to detect Alzheimer's disease and brain tumors from brain imaging data with high accuracy and efficiency. Alzheimer's disease and brain tumors remain among the most challenging neurological disorders to diagnose at an early stage due to the subtle nature of their early symptoms and complex imaging patterns. Manual diagnosis by radiologists can be time-consuming, prone to errors, and requires significant expertise and reducing the burden on medical systems. By adopting a transfer learning approach, the need for large-scale labeled medical datasets is reduced, making the model more practical for real-world deployment. Furthermore, the improved performance of the VGG19-based model demonstrates the capability of deep CNNs in complex medical imaging tasks. The system can act as a valuable clinical decision support tool, particularly in remote or under-resourced healthcare environments, thereby extending the reach and efficiency of quality healthcare services.

2. LITERATURE SURVEY

Hon and Khan [1] proposed a transfer learning approach. It was introduced by using the two most famous deep CNN architectures (Inception and VGG16) with the already trained and fine-tuned weights of ImageNet data. Using a pre-trained model on ImageNet, the researchers trained the last fully connected layer with a small number of training MRI scans. To overcome the over-fitting of the small training dataset, image entropy was applied to MRI images, to extract the most informative portions. An OASIS cross-sectional dataset with 416 subjects was used in an experiment aimed at the binary classification of AD. Five-fold cross-validation was applied with an 80 percent and 20 percent split between training and testing in the fully connected layer retraining. To compare the results VGG16 was also trained from scratch, as well as with transfer learning. Due to the small training set, the VGG16 trained from scratch performed less well in terms of accuracy, 74.12%, while the VGG16 with transfer learning provided 92.3% accuracy. Finally, Inception V4 was used with transfer learning that provided promising results with 96.25% accuracy. Sarraf and Tofighi [2] utilized CNN with LeNet-5 was utilized for the classification of the brain with AD and the normal brain, by using functional MRI 4D data. In the first step, the 4D data was transformed into 2D by using the neuroimaging packages Nibabel and OpenCV. Then, 2D images were labeled as AD vs NC. The LeNet model, based on CNN, was then used for the binary classification of the images. The results were compared with the famous support vector machine model and, in contrast to it, the proposed model provided better results, with 96.86% accuracy. Liu et al. [3] proposed a framework with the combination of sparse auto-encoders (SAEs) and a softmax logistic regression was used, along with autoencoders, to use unlabeled data. Two data sets, MR and positron emission tomography (PET) from the ADNI database, were used. The main target of this research was to use SAE for high-level feature selection in the unsupervised pre-training stage. As a result of two different neuroimaging modalities, a zero-masking technique was used for the extraction of complimentary details from these different datasets. Features extracted from SAE, using unsupervised data, were then manipulated with a softmax regression. The performance of the model was tested on the classification of AD. In comparison with other advanced models, like SVM and other deep learning methods, the proposed model performed very well with 91.4 percent accuracy just because of its capability to extract features in one setting and its requiring of less labeled data. Liu et al. [4] customized 2D-CNN model, with 9 depth-wise separable convolutional and normalization layers, was used, along with Inception V3 and Xception models for transfer learning. In this research, the classification of AD patients, class imbalance, and data leakage issues were discussed. The second fully connected layer used the sigmoid function as an activation function to categorize the data into two classes. An OASIS dataset, with T1-

weighted structural MRI images, was used and the dataset was divided into 3 portions: set 1, set 2, and set 3. Cross-validations with 2-folds, 5-folds, and 9-folds were applied to the partitioned datasets, respectively. Dataset 1 was used for the prediction of AD, dataset 2 was used for class imbalance and dataset 3 was used for data leakage problems. For the AD classification on dataset 1, 45 subjects were used for training and validation purposes. Stochastic gradient descent (SGD) was used as an optimization algorithm. For loss function, binary cross entropy was used. In comparison with other deep learning models, the proposed model, which was based on transfer learning, provided promising results.

Tufail et al. [5] developed a deep learning framework with a softmax output layer and stacked autoencoders are used for the detection of Alzheimer's disease and its initial stage MCI. MRI data of 311 patients available on the ADNI database was used. Gray matter (GM) was extracted from the MRI images, which made the baseline for the detection of MCI and the CMRGlc patterns using PET. Elastic Net is then used to extract the high-level features. In individual cross-fold, 90 percent of subjects are used for training and the rest of the 10 percent for testing. SK-SVM and MK-SVM are considered for comparison with the proposed model. The model gives 87.76 % accuracy in the binary classification of AD patients. Liu et al. [6] employed AlexNet, a fine-tuned pre-trained CNN, was used for the binary and multi-class classification of 3D MRI images. The proposed model was trained on the already pre-processed data in which WM, GM, and CSF were segmented and, then, the testing of the model was conducted on the unsegmented 3D MRI scans of the human brain. An OASIS dataset, consisting of 382 subjects, was used for training and testing. After the training of the proposed model on the segmented dataset, the retrained convolutional neural network was then used for the validation over the unsegmented 3D MRI images. For multi-class classification, the proposed model outperformed the binary classification, with 92.8% accuracy versus 89.6%.

Maqsood et al. [7] proposed a modified Siamese CNN model, inspired by Oxford Net (VGG16), was used for the classification of AD stages. The basic idea behind the proposed model was to use the augmentation technique, with an extra convolutional layer in VGG16. Augmentation was applied to an OASIS dataset after the pre-processing phase. Two parallel layers of modified VGG16 worked for the extraction of the most important features. Batch normalization was applied to increase the learning rate, which gradually decreased, due to changing the parameter in individual layers of the CNN model. In comparison with the other state-of-the-art models, the proposed model provided 99.05 % accuracy, and it also reduced the problems of over-fitting and regularization. In [7], a layer-wise transfer learning approach and tissue segmentation were used for the classification of AD. The dataset used in this research was collected from the ADNI database. In the pre-processing step, the skull stripping, and extraction of GM, WM, and CSF were conducted using SPM12. The VGG-19 network was customized by modifying the last two fully connected and classification layers. Instead of freezing the trained fully connected layers, the researchers divided the model into two groups and then they gradually fixed CNN layers in different blocks. The training of the proposed model was done on both augmented and non-augmented datasets. In the first group, 8 CNN layers with 3 max-pooling layers were kept fixed, and in the second group 12 CNN layers along with 4 max-pooling layers were kept fixed. In experiments after the augmentation, the classification results of the proposed model were 98.73%, 83.72%, and 80% on AD vs NC, EMCI vs LMCI, and other classes, respectively. Mehmood et al. [8], a cross-model technique, using the transfer learning technique, was used to reduce the over-fitting problem, while the training was done on a small set of MRI images. The proposed model was trained on the structural MRI data collected from the ADNI database and then tested on the DTI dataset. The outcome of the model on the two different cross-modalities was outstanding, with 92 percent accuracy on NC vs AD, 80 percent on NC vs MCI, and 85 percent on MCI vs AD. Mehmood et al. [9] employed the deep learning models, GoogLeNet and ResNet, were trained from scratch on structural MRI data sets available on the ADNI database. The main target of this research was to segment the gray matter (GM) and then train the CNN networks on these segmented GM images. The addition of the augmentation layer proved to be a useful step in the classification of the four stages of AD. Qiu et al. [10] developed an a convolutional network, with some extra parameters like gender, Mental-state exam score, and age, were trained on different datasets. The first data set was composed of clinically diagnosed Alzheimer's patients and the second data set was extracted from the ADNI. The validation of the model was done on three different datasets, which included Australian Imaging, Biomarker and Lifestyle Flagship Study of Ageing, and the National Alzheimer's Coordinating Center. The outcome of the model on multi-modal datasets was good in comparison to the other CNN models. Ramzan et al. [11] utilized ResNet18 is used for the classification of AD stages. The main purpose of this research was to utilize the Resting-state fMRI data, extracted from the ADNI database, which is a very useful neuroimaging technology used for the observation of neurodegenerative diseases. The concept of transfer learning was applied to the convolutional model, which was trained from scratch. The results of the proposed model were extracted with and without augmentations. They were also compared with other advanced CNN models. The outcomes of the proposed model showed promising results in the classification of AD stages.

3. PROPOSED SYSTEM

The Alzheimer's Detection project leverages deep learning techniques to identify brain tumors associated with Alzheimer's disease using DICOM medical images. Users begin by uploading a directory of DICOM images labeled as either 'Normal' or 'Alzheimer Brain Tumor.' These images undergo preprocessing, including resizing and conversion into numerical arrays for analysis. The system utilizes two convolutional neural network (CNN) architectures—VGG16 as the existing model and VGG19 as the proposed model—to train and test on the preprocessed data. Both models are evaluated using key performance metrics such as accuracy, precision, recall, and F1-score, with results visualized through graphs. Additionally, the application supports real-time testing by allowing users to upload new DICOM images, which are then classified using the trained VGG19 model to predict the presence of Alzheimer's-related brain tumors.

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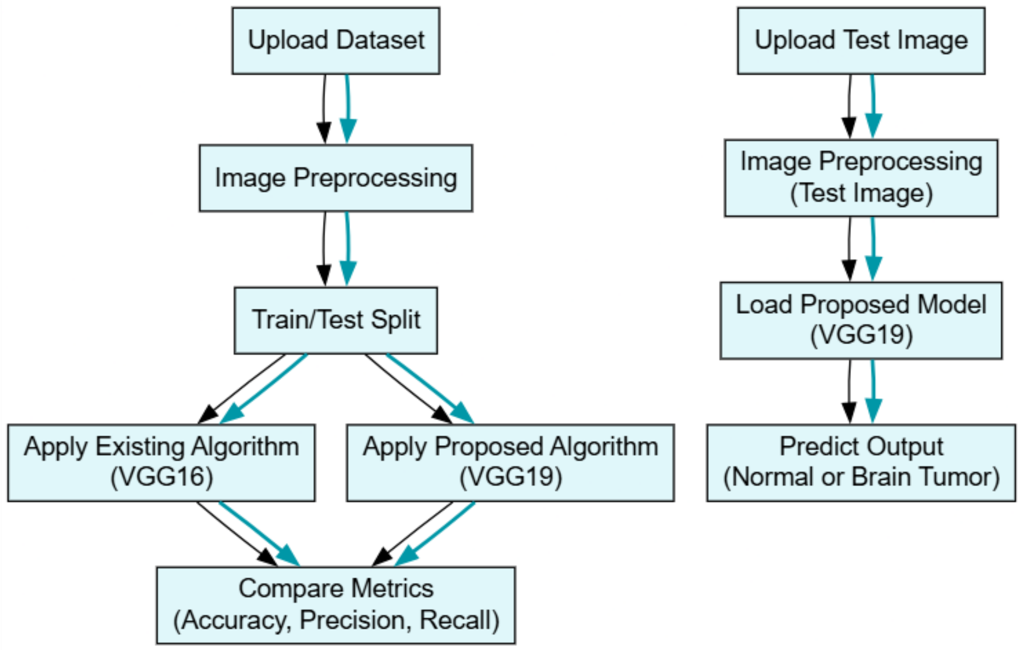


Figure 2: Block Diagram of Proposed System.

Uploading Dataset: Upon clicking the "Upload Dicom Alzheimer Brain Dataset" button, the user is prompted to select a directory containing DICOM images related to Alzheimer's disease and brain tumors. This dataset typically includes images labeled as 'Normal' or 'Alzheimer Brain Tumor'.

Image Preprocessing: After uploading the dataset, the program preprocesses the images. This involves reading each DICOM image, resizing it to a standard size (e.g., 32x32 pixels), converting it into a numerical array format, and associating each image with its corresponding label ('Normal' or 'Alzheimer Brain Tumor'). These preprocessed images and their labels are then stored for further use.

Training and Testing VGG16 Model: The program trains and tests a pre-existing VGG16 convolutional neural network (CNN) model using the preprocessed image data. The VGG16 model is trained to classify images into the two categories: 'Normal' or 'Alzheimer Brain Tumor'. The training process involves optimizing the model's parameters to minimize classification errors, while the testing process evaluates the model's performance on unseen data.

Training and Testing VGG19 Model: Similarly, the program trains and tests a proposed VGG19 CNN model using the same preprocessed image data. The VGG19 model architecture is similar to VGG16 but with deeper layers, potentially leading to improved performance in image classification tasks. The training and testing procedures for the VGG19 model are similar to those for the VGG16 model.

Model Evaluation Graphs: The program generates graphs to visualize the training progress and performance of both the VGG16 and VGG19 models. These graphs may include metrics such as accuracy, precision, recall, and F1-score over multiple epochs of training. These metrics help assess the models' performance and identify any potential issues such as overfitting or underfitting.

Test Image Prediction using VGG19 Model: Finally, the program allows users to upload a test DICOM image for tumor detection using the trained VGG19 model. The model predicts whether the uploaded image contains a brain tumor associated with Alzheimer's disease. The prediction is displayed along with the uploaded image, providing a quick assessment of the model's performance on unseen data.

3.2 Data Preprocessing

Image preprocessing is a critical step in computer vision and image analysis tasks. It involves a series of operations to prepare raw images for further processing by algorithms or neural networks. Here's an explanation of each step in image preprocessing:

Step 1. Image Read: The first step in image preprocessing is reading the raw image from a source, typically a file on disk. Images can be in various formats, such as JPEG, PNG, BMP, or others. Image reading is performed using libraries or functions specific to the chosen programming environment or framework. The result of this step is a digital representation of the image that can be manipulated programmatically.

Step 2. Image Resize: Image resize is a common preprocessing step, especially when working with machine learning models or deep neural networks. It involves changing the dimensions (width and height) of the image. Many machine learning models, especially convolutional neural networks (CNNs), require input images to have the same dimensions. Resizing allows you to standardize input sizes. Smaller images require fewer computations, which can be beneficial for faster training and inference. In some cases, images need to be resized to fit within available memory constraints. When resizing, it's essential to maintain the aspect ratio to prevent image distortion. Typically, libraries like OpenCV or Pillow provide convenient functions for resizing images.

Step 3. Image to Array: In this step, the image is converted into a numerical representation in the form of a multidimensional array or tensor. Each pixel in the image corresponds to a value in the array. The array is usually structured with dimensions representing height, width, and color channels (if applicable). For grayscale images, the array is 2D, with each element representing the intensity of a pixel. For color images, it's a 3D or 4D array, with dimensions for height, width, color channels (e.g., Red, Green, Blue), and potentially batch size (if processing multiple images simultaneously). The conversion from an image to an array allows for numerical manipulation and analysis, making it compatible with various data processing libraries and deep learning frameworks like NumPy or TensorFlow.

Step 4. Image to Float32: Most machine learning and computer vision algorithms expect input data to be in a specific data type, often 32-bit floating-point numbers (float32). Converting the image array to float32 ensures that the pixel values can represent a wide range of intensities between 0.0 (black) and 1.0 (white) or sometimes between -1.0 and 1.0, depending on the specific normalization used. The step is essential for maintaining consistency in data types and enabling compatibility with various machine learning frameworks and libraries. It's typically performed by dividing the pixel values by the maximum intensity value (e.g., 255 for an 8-bit image) to scale them to the [0.0, 1.0] range.

Step 5. Image to Binary: Image binarization is a process of converting a grayscale image into a binary image, where each pixel is represented by either 0 (black) or 1 (white) based on a specified threshold. Binarization is commonly used for tasks like image segmentation, where you want to separate objects from the background. The process involves setting a threshold value, and then for each pixel in the grayscale image, if the pixel value is greater than or equal to the threshold, it is set to 1; otherwise, it is set to 0. Binarization simplifies the image and reduces it to essential information, which can be particularly useful in applications like character recognition or object tracking, where you need to isolate regions of interest.

3.3 Model Build and Train

3.3.1 VGG19 Model

The VGG19 model, short for Visual Geometry Group 19-layer model, is a convolutional neural network (CNN) architecture proposed by the Visual Geometry Group at the University of Oxford. It gained prominence for its simplicity and effectiveness in image classification tasks. VGG19 is an extension of the earlier VGG16 model, with deeper layers resulting in improved performance on various visual recognition tasks.

The architecture of VGG19 can be visualized as a sequence of convolutional layers followed by max-pooling layers, culminating in fully connected layers for classification.

Here is a simplified block diagram illustrating the key components of VGG19:

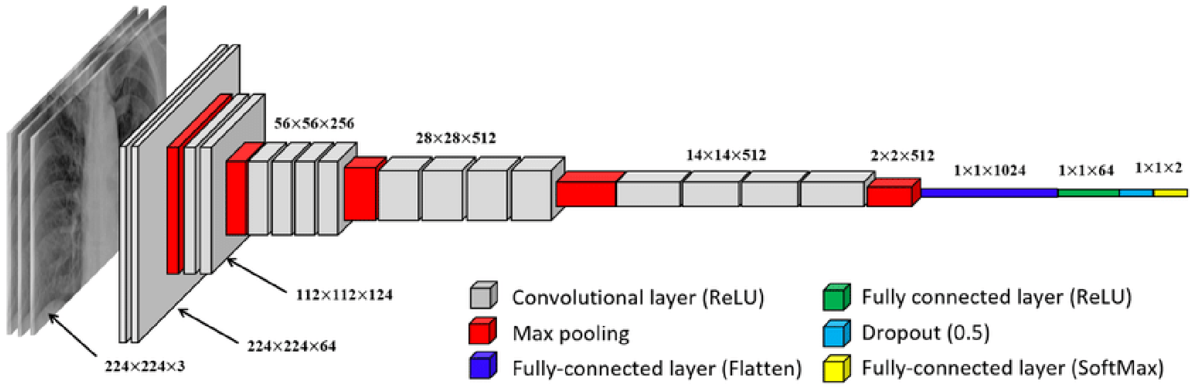


Figure 3: Architecture diagram of VGG19 model.

VGG19 operates by passing the input image through a series of convolutional layers interspersed with max-pooling layers. These convolutional layers are responsible for extracting features at different levels of abstraction. Each convolutional layer applies a set of filters to the input image, detecting various patterns such as edges, textures, and shapes.

The max-pooling layers serve to downsample the feature maps, reducing their spatial dimensions while retaining the most salient information. This downsampling helps in reducing computational complexity and mitigating overfitting. As the input image progresses through the network, the feature maps become increasingly abstract and complex, capturing higher-level representations of the input image.

After passing through several convolutional and max-pooling layers, the output is flattened and fed into a series of fully connected layers. These fully connected layers perform high-level reasoning and decision-making based on the extracted features, ultimately producing a probability distribution over the possible classes. The final layer typically employs a softmax activation function to convert the raw output into a probability distribution, indicating the likelihood of the input image belonging to each class in the dataset.

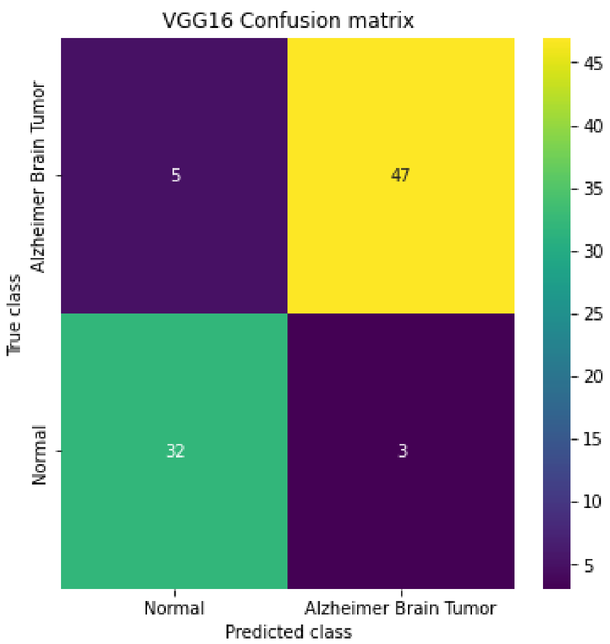
4. RESULTS AND DESCRIPTION

4.1 Dataset description

The dataset for the "Alzheimer Brain Tumor Detection using VGG16 & VGG19 Algorithms" project typically consists of brain MRI images used for classifying conditions like Alzheimer's disease or brain tumors. These MRI scans are often grayscale images that represent cross-sectional slices of the brain, captured in 2D or 3D. The dataset may include labels such as "Normal" for healthy brain scans and "Tumor" for those showing the presence of brain tumors, possibly associated with Alzheimer's or other neurological conditions. The images are resized to a fixed size (e.g., 224x224 pixels) to be compatible with deep learning models like VGG16 and VGG19. Pixel values are usually normalized to a range between 0 and 1 to facilitate model training. The dataset is typically split into training and testing sets, with around 80% of the data used for training the model and the remaining 20% for testing its performance on unseen data. Data augmentation techniques such as rotation, flipping, and zooming may be applied to enhance the training set and prevent overfitting. Example publicly available datasets include the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, the Kaggle Brain Tumor Dataset, and the BraTS dataset, which provide labeled MRI scans of patients with Alzheimer's or brain tumors. Ethical considerations around data privacy and patient confidentiality are critical when using such datasets, particularly if they involve personally identifiable information, requiring adherence to regulations like HIPAA or other privacy guidelines. The dataset size can vary, typically ranging from hundreds to thousands of images, and handling any class imbalance may require techniques like SMOTE or class weighting to improve model accuracy.

4.2 Results description

Figure 4 Displays the confusion matrix of the VGG16 model. The confusion matrix is a table that describes the performance of a classification model, showing the counts of true positive, true negative, false positive, and false negative predictions at the same time VGG 19 Shows the confusion matrix of the VGG19 model. Similar to Figure 4, this matrix provides insights into the classification performance of the VGG19 model on a specific dataset.



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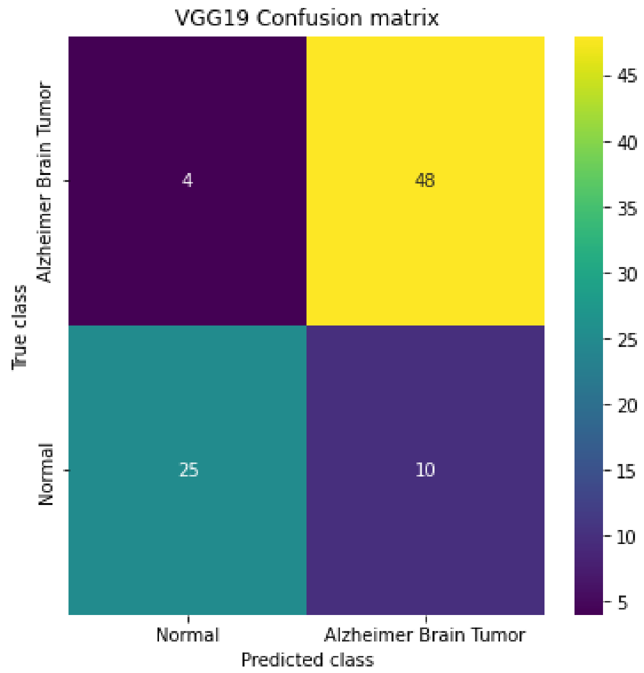
(a)



(b)

Fig 4: Confusion matrices for Existing VGG 16 and Proposed VGG19

Figure 5 Illustrates an accuracy comparison graph between the VGG16 and VGG19 models. This graph compares the accuracy scores of the two models across different evaluation metrics or datasets.

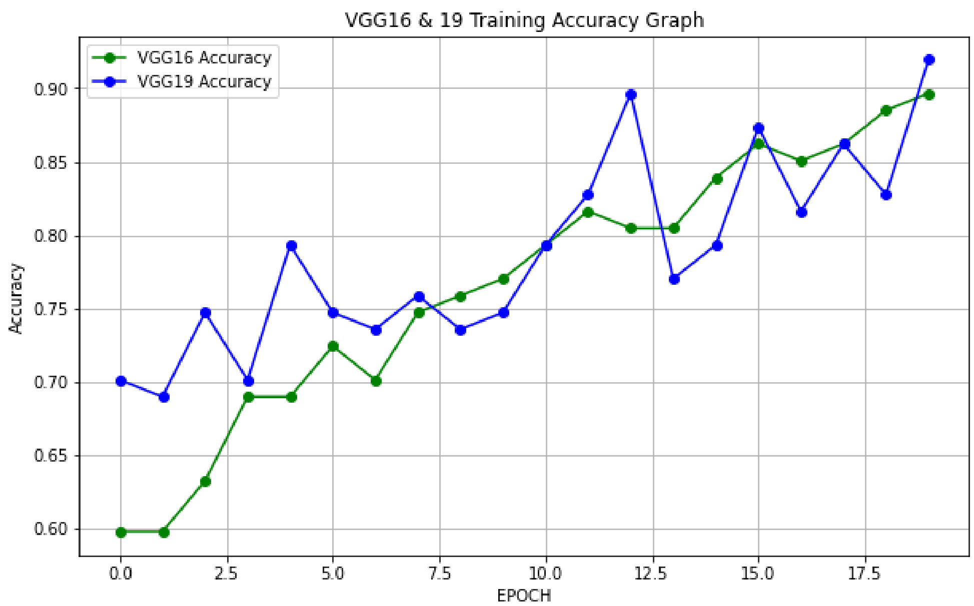


Figure 5: Shows the Accuracy Comparison graph of VGG16 and VGG19 models

Figure 6 Presents the model predictions of brain tumors on the test data. This figure show examples of images from the test set along with the corresponding predictions made by the model, indicating whether a brain tumour is present or not.

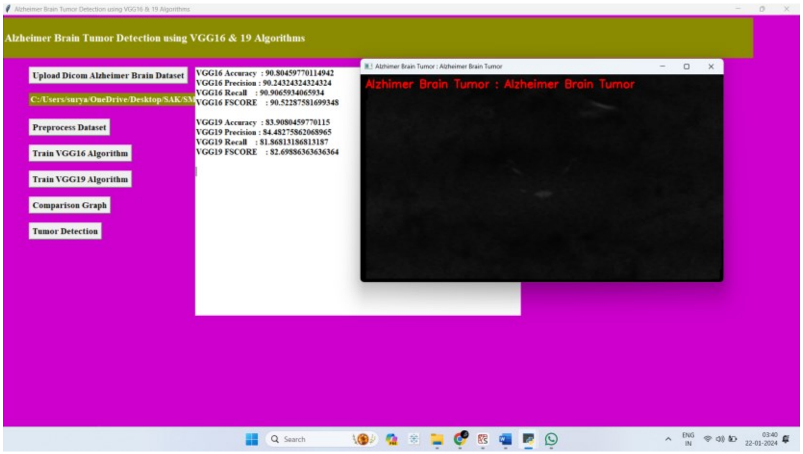


Figure 6: Shows the model prediction of brain tumor on test data.

Table 1: Performance comparison of quality metrics obtained using VGG16

And VGG19 model.

Model	VGG16	VGG19
Accuracy (%)	83.9	90.8
Precision (%)	84.4	90.2
Recall (%)	81.8	90.8
F1-score (%)	82.6	90.5

Table 1 shows both the VGG19 and VGG16 convolutional neural network models were trained and evaluated for the detection of Alzheimer-related brain tumors using DICOM image data. The VGG19 model outperformed VGG16 across all major evaluation metrics, indicating its superior capability in handling this medical image classification task. Specifically, VGG19 achieved an accuracy of 90.8%, demonstrating high correctness in classifying brain scans into 'Normal' or 'Alzheimer Brain Tumor' categories. It also recorded a precision of 90.2%, reflecting a low rate of false positives, which is critical in avoiding misdiagnosis. The recall was 90.8%, indicating the model's strong ability to detect actual tumor cases without missing many, and the F1-score was 90.5%, representing a balanced trade-off between precision and recall. The VGG16 model, while still effective, showed relatively lower performance. It attained an accuracy of 83.9%, suggesting it was less consistent in prediction compared to VGG19. The precision stood at 84.4%, which implies a slightly higher false positive rate than VGG19. The recall was 81.8%, indicating a moderate chance of missing some actual positive cases, and the F1-score was 82.6%, reflecting a less optimal balance between detecting actual cases and avoiding false alarms. Overall, these results highlight the VGG19 model's deeper architecture as a contributing factor to its enhanced classification performance, making it more suitable for critical diagnostic applications involving Alzheimer's and brain tumor detection.

5. CONCLUSION

The research delves into the transformative potential of transfer learning models in the early detection of Alzheimer's disease and brain tumors, presenting a paradigm shift from traditional diagnostic methods. The limitations of time-consuming and subjective visual inspection are addressed through the application of deep learning algorithms, leveraging transfer learning techniques. By harnessing the knowledge embedded in pre-trained models, these algorithms demonstrate remarkable efficiency in processing extensive medical image data, particularly MRI scans. The research highlights the significant strides made in automating and enhancing the detection process for these debilitating neurological conditions. The amalgamation of advanced machine learning techniques with medical imaging not only promises early intervention but also holds the key to improving patient care and overall healthcare system efficiency.

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