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International Journal for Modern Trends in Science and Technology
Volume 11, Issue 09, pages 34-41.
ISSN: 2455-3778 online
Available online at: http://www.ijmtst.com/vol11issue09.html
DOI: https://doi.org/10.5281/zenodo.17148904

Alzheimer's & Brain Tumor Detection : Deep Learning with VGG-16 & VGG-19 Algorithms

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To Cite this Article
P. Swathi, G. Uma Maheswari, Ch. Madhu Kalpana & M. Pallavi2 (2025). Alzheimer's & Brain Tumor Detection : Deep Learning with VGG-16 & VGG-19 Algorithms. International Journal for Modern Trends in Science and Technology, 11(09), 34-41. https://doi.org/10.5281/zenodo.17148904

Article Info
Received: 07 August 2025; Accepted: 31 August 2025.; Published: 05 September 2025.

KEYWORDS

Alzheimer's disease, Brain tumor detection, Deep learning, VGG16, VGG19, Convolutional Neural Networks, MRI, Transfer Learning.

ABSTRACT

The early and accurate detection of neurological diseases such as Alzheimer's disease and brain tumors is vital for patient prognosis and treatment planning. Magnetic Resonance Imaging (MRI) provides high-quality images of brain structures, which are crucial for disease diagnosis. In this study, deep learning techniques were applied to automate the classification of MRI images into Alzheimer's disease and brain tumor categories. Two wellknown Convolutional Neural Network (CNN) architectures, VGG16 and VGG19, were utilized through transfer learning to enhance classification accuracy. The dataset consisted of preprocessed brain MRI images, resized to 224×224 pixels, and data augmentation techniques were employed to improve the models' robustness. Experimental results demonstrated that VGG19 achieved a classification accuracy of 96.3%, outperforming VGG16's 95.7% accuracy. This research highlights the practical application of CNN-based automated systems for clinical decision support, significantly aiding radiologists and clinicians.

1. INTRODUCTION

Neurological diseases such as Alzheimer's disease and brain tumors continue to poseserious health risks globally. These conditions lead to significant cognitive impairment, functional disabilities, and often fatal outcomes if left undetected.Accurate and timely diagnosis plays a crucial role in improving patient prognosis and treatment planning.

Magnetic Resonance Imaging (MRI) has become an essential, non-invasive imaging modality for visualizing brain structures. It provides detailed images that help radiologists identify abnormalities, lesions, or degenerative changes. However, manual interpretation of MRI scans can be labor-intensive and prone to diagnostic errors.

The rise of artificial intelligence, particularly deep learning, has transformed medical imaging diagnostics.Convolutional Neural Networks (CNNs) have shown remarkable success in automatically detecting complex patterns in medical images. These models have the potential to reduce human error and increase diagnostic accuracy.

This research aims to apply deep learning techniques using VGG16 and VGG19 CNN architectures for classifying

brain MRI images. The study compares the performance of both models in detecting Alzheimer's disease and brain tumors. Results from this study highlight the potential of AI-based systems in clinical decision support applications.

1.1. Objectives:

◎ 1. To preprocess and augment a publicly available MRI image dataset for enhanced deep learning model performance.

◎ 2. To implement and fine-tune VGG16 and VGG19 CNN architectures using transfer learning to adapt them for

binary classification of Alzheimer's disease and brain tumors.

◎ 3. To evaluate and compare the classification accuracy, precision, recall, and F1-score metrics of both models.

◎ 4.To propose a reliable, efficient, and automated deep learning pipeline capable of assisting healthcare professionals in the diagnosis of neurological diseases.

1.2.Principles Used :

1. **Convolutional Neural Networks (CNNs):**CNNs are a class of deep learning models designed to process data with a grid-like topology, such as images. They automatically learn hierarchical feature representations through convolution, pooling, and activation functions.

2. **Transfer Learning:** Transfer learning involves reusing a pre-trained model on a new but related task. In this study,

VGG16 and VGG19 models pre-trained on ImageNet were fine-tuned for classifying brain MRI images.

3. **Data Augmentation:**To improve model generalization and avoid overfitting,data augmentation techniques like rotation, flipping, and zooming were applied. This artificially increases dataset diversity without collecting new images.

4. **Performance Evaluation Metrics:**Standard metrics such as accuracy, precision, recall, and F1-score were used to assess model performance. Confusion matrices provided detailed insights into classification errors and diagnostic reliability.

5.Image Preprocessing: Before training, all MRI images undergo preprocessing steps such as resizing to a fixed dimension, normalization of pixel values, and noise reduction. This ensures data consistency, improves computational efficiency, and enhances the accuracy of deep learning models.

1.3. Processes Involved:

1. Data Collection:A publicly available brain MRI dataset was collected containing images categorized into Alzheimer's disease and brain tumor cases. This dataset served as the foundation for training and testing the deep learning models.

2. Image Preprocessing: All MRI images were resized to 224×224 pixels, normalized, and cleaned to ensure consistent image dimensions and quality. Data augmentation techniques like flipping, rotation, and zooming were applied to enhance dataset variety and prevent overfitting.

3. Model Selection: Two popular CNN architectures, VGG16 and VGG19, were selected for this study due to their proven performance in image classification tasks. Both models were implemented using transfer learning by utilizing pre-trained ImageNet weights.

4. Transfer Learning and Fine- Tuning: The pre-trained VGG16 and VGG19 models were fine-tuned for

binary classification by replacing their final fully connected layers. The models3 were retrained on the MRI dataset while retaining learned features from ImageNet.

5. Model Training: The models were trained using Python and TensorFlow on a high-performance GPU system. Training involved multiple epochs with optimized learning rates, batch sizes, and validation splits to ensure effective

learning.

6. **Performance Evaluation:**Both models were evaluated using classification metrics such as accuracy, precision, recall, and F1-score. Confusion matrices were also generated to visualize classification performance and misclassification rates.

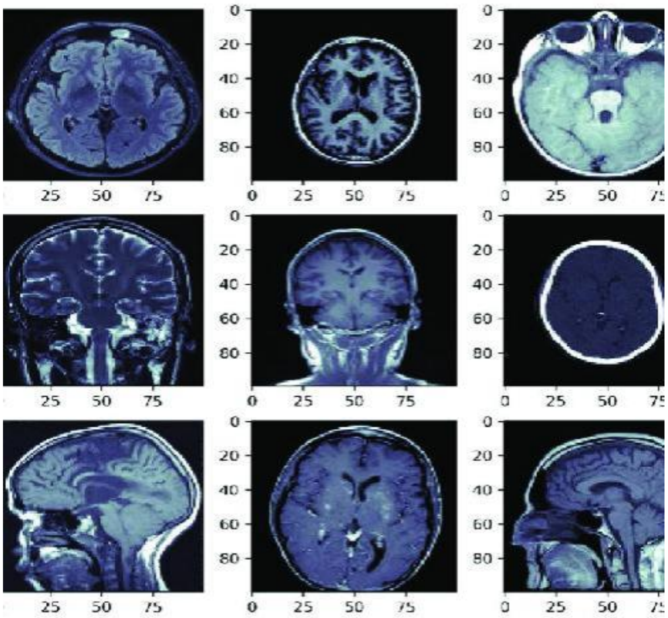


Fig1.: Brain MRI Images

7. Comparative Analysis: The performance results ofVGG16 and VGG19 were compared to identify the more effective model for this diagnostic task. VGG19 demonstrated slightly better accuracy and reliability in classification.

8. Result Interpretation and Conclusion: The findings were analyzed, discussed, and documented, highlighting the practical application of deep learning in medical image diagnosis. Recommendations for future work and systemimprovements were proposed.

9 .Conclusion and Recommendations : Based on experimental findings, conclusions are drawn regarding model effectiveness, and suggestions are made for future improvements such as exploring other CNN architectures like ResNet, DenseNet, or MobileNet.

1.5.Materials & Methods

This study used MRI datasets for Alzheimer's and brain tumor detection, preprocessed and resized for compatibility with VGG16 and VGG19 models. Transfer learning was applied using these pre-trained architectures, and models were trained and evaluated using standard deep learning techniques in Python with TensorFlow.

a)Materials:

1. **Dataset used**: This study used two MRI datasets from Kaggle—one for Alzheimer's classification with four stages (Non-Demented, Mild, Moderate, and Very Mild Demented) and another for binary brain tumor detection (Tumor vs.No Tumor).These datasets, with their diversity and complexity, were ideal for training deep learning models and capturing essential features for accurate classification.

2. **Image Format and Dimensions**: All MRI images wereresized to 224×224 pixels and converted to RGB format to match the input size required by the VGG architectures. This resizing ensured consistency across the datasets, reducing computational load while preserving the key visual features needed for accurate classification by the models.

3. **Software and Libraries:** The project was implemented in Python using Google Colab and Jupyter Notebook for efficient execution. TensorFlow and Keras were used to build andtrain deep learning models, while libraries such as NumPy, Pandas, OpenCV, and Pillow assisted with data manipulation, image processing, and augmentation. Matplotlib and Seaborn provided essential tools for visualizing model performance and training progress, and Scikit-learn was used for evaluation metrics.

4. **Hardware Specifications:** Model training and evaluation were performed on GoogleColab, leveraging GPU acceleration with NVIDIA Tesla K80 and T4 units for faster computations. For development and initial testing, a local machine with at least 16 GB of RAM and a mid-range GPU like NVIDIA GTX 1650 was used, providing sufficient power for smaller scale experiments.

5. **Pre-trained Models:**The VGG16 and VGG19 models, pre-trained on ImageNet, were used as the foundation for transfer learning. These models' deep convolutional layers, pre-trained on a vast variety of images, enabled feature extraction from MRI scans, which helped reduce training time while boosting performance and accuracy in classifying medical images.

b)Methods:

1. **Data Preprocessing:** The MRI images were normalizedby scaling pixel values to the [0,1] range, making them suitable for neural network input. Data augmentation techniques, including random rotations, flipping, zooming, and brightness adjustments, were applied to simulate real-world variability and increase the dataset's diversity. This helped prevent overfitting

by introducing a variety of transformations during model training.

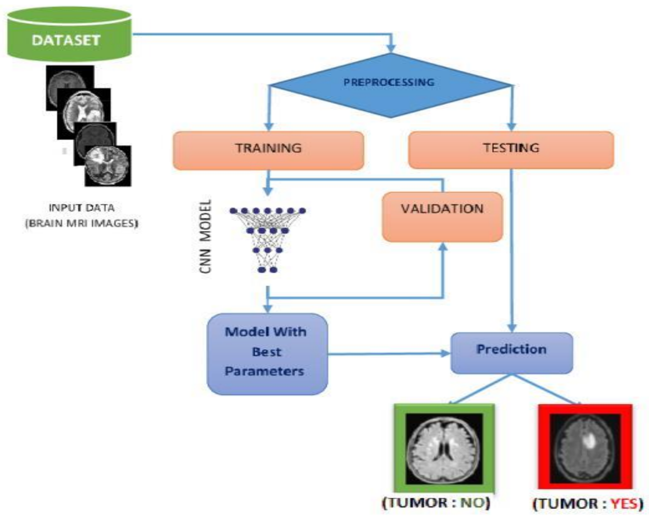
2. **Model Architecture:** For both Alzheimer's and brain tumor detection, the VGG16 and VGG19 architectures were adapted using transfer learning. The original fully connected layers were removed and replaced with custom dense layers specific to each classification task. Dropout layers were added to reduce overfitting, and the models were finalized with softmax layers for multi-class and binary classification, respectively. The convolutional layers
were initially frozen to retain prelearned features.

3. **Model Compilation and Training:** The models were compiled using the Adam optimizer with a learning rate of 0.0001. For the Alzheimer's dataset, categorical cross-entropy loss was used, while binary cross-entropywas
used for the brain tumor dataset. Training was conducted over 25 to 50 epochs, with a batch size of 32, and included a 20% validation split for model evaluation. Early stopping was implemented to prevent overfitting by halting training when validation accuracy plateaued.

4. **Evaluation Metrics:**Model performance was evaluated using accuracy, precision, recall, and F1-score, with confusion matrices generated to analyze true positives, false positives, true negatives, and false negatives. For the binary
classification task (brain tumor detection), ROC-AUCcurves were plotted to assess the model's ability to distinguish between classes, particularly in the presence of class imbalances.

4. **Visualization and Analysis:**Training history graphs, including loss and accuracy curves over epochs, were plotted to monitor model performance. Confusion matrices were visualized using Seaborn heatmaps to provide a clearer interpretation of classification outcomes. Additionally, a selection of predictions were displayed alongside true labels to identify misclassified cases and assess model limitations for further improvement.

c)Block Diagram



2. EXPERIMENTAL METHODOLOGY

The proposed system for the automated classification of Alzheimer's disease and brain tumors using brain MRI images follows a carefully structured deep learning pipeline consisting of multiple interconnected processes. The overall workflow begins with data collection, where a publicly available MRI dataset is selected for its diversity, clinical relevance, and high- resolution images. Ensuring a reliable, well- annotated dataset is crucial, as deep learning models are highly sensitive to data quality and variability. Once the data is acquired, it undergoes a series of preprocessing operations designed to prepare the images for the neural networks. Each MRI image is resized to a standard dimension of 224×224 pixels to align with the input requirements of the VGG16 and VGG19 architectures. Furthermore, normalization is performed to adjust pixel
intensity values into a consistent range, typically between 0 and 1, thereby stabilizing the training process and improving convergence rates. To enhance the robustness of the models, data augmentation techniques such as random
rotations, horizontal and vertical flipping, zooming, and cropping are applied. This process artificially expands the dataset by generating multiple modified versions of each image, reducing the risk of overfitting and allowing the model to generalize better to unseen data.

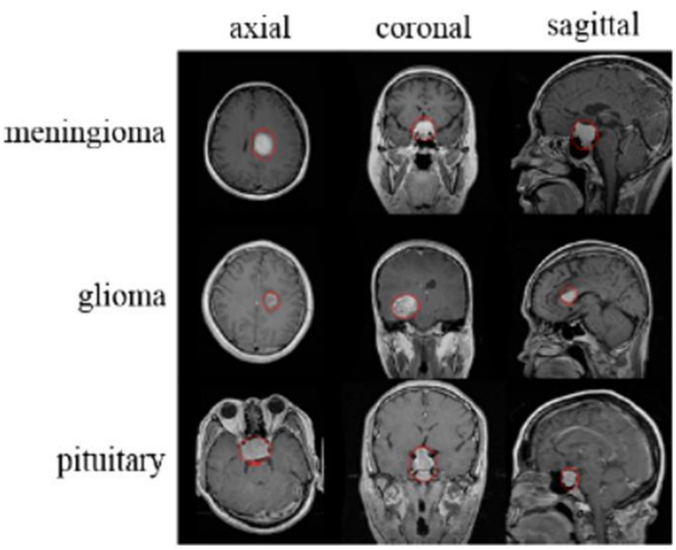


Fig 2 Brain Tumor Images

Following preprocessing, feature extraction is performed using two prominent convolutional neural network (CNN) architectures, VGG16 and VGG19. These6 models are widely recognized for their effective hierarchical feature extraction capabilities in image classification tasks. Originally trained on the ImageNet dataset containing millions of images across 1,000 categories, both models are adapted to this medical imaging application through transfer learning. In this approach, the lower convolutional layers of VGG16 and VGG19, which capture general image features such as edges, curves, and textures, are retained, while the upper fully connected layers responsible for classification are replaced with custom dense layers tailored for this binary classification task. The final classification head is designed to output two classes: Alzheimer's disease and brain tumors. The VGG16 architecture comprises 16 weight layers, including convolutional, pooling, and fully connected layers, while VGG19 extends this structure with three additional convolutional layers, totaling 19 weight layers. Both networks progressively extract deeper, more abstract features from MRI images, enabling accurate identification of subtle patterns characteristic of neurological abnormalities.

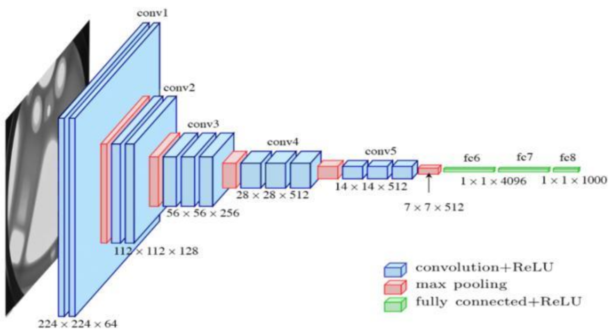


Fig 3Architecture Model for VGG 16 & 19

The training phase represents a critical component of the methodology, where the modified VGG16 and VGG19 models are exposed to the preprocessed and augmented MRI dataset. During training, the models learn to adjust their internal weights through iterative forward and backward propagation processes to minimize classification errors. The Adam optimizer is employed due to its computational efficiency, adaptive learning rate adjustments, and robustness against noisy gradients. The training configuration includes a ReLU (Rectified Linear Unit) activation function to introduce nonlinearity, enabling the network to model complex decisionboundaries between the two diagnostic categories. To mitigate overfitting, dropout regularization is applied to the dense layers, where a random subset of neurons is deactivated during each training iteration. Furthermore, L2 regularization with a coefficient of 0.0006 penalizes large weight values, promoting model generalization. The total number of neurons in the dense layer is set to 100, and the models are trained over 100 epochs using a mini-batch approach, allowing the networks to iteratively refine their parameters for optimal classification performance.

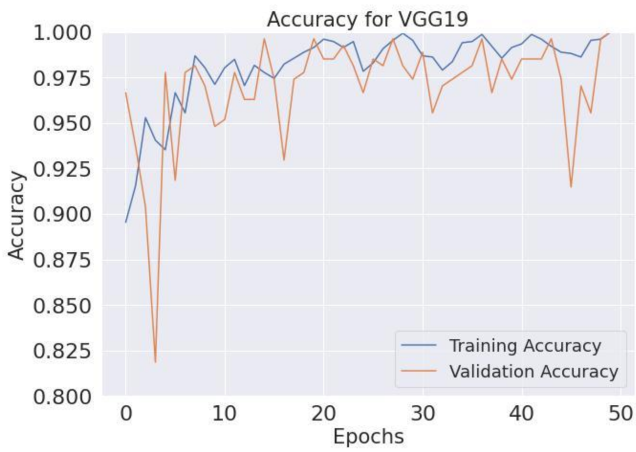


Fig4: Training & Accuracy

Once the models are trained, their performance iscomprehensively evaluated using a range of classification metrics to ensure diagnostic reliability.

These metrics include accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic (AUC-ROC) curve. Accuracy measures the proportion of correctly7 classified MRI images, while precision assesses the proportion of true positive predictions among all positive predictions made by the model. Recall evaluates the model's ability to identify all actual positive cases, and the F1-score balances precision and recall, offering a single, reliable indicator of model performance. Additionally, the ROC curve plots the true positive rate against the false positive rate at various threshold settings, providing a

visual assessment of the model's diagnostic discrimination ability. Higher AUC values, ideally approaching 1.0, indicate superior model capability in distinguishing between Alzheimer's and brain tumor cases. This multi-metric evaluation framework ensures a well-rounded, clinically relevant performance assessment for both VGG16

and VGG19 models.

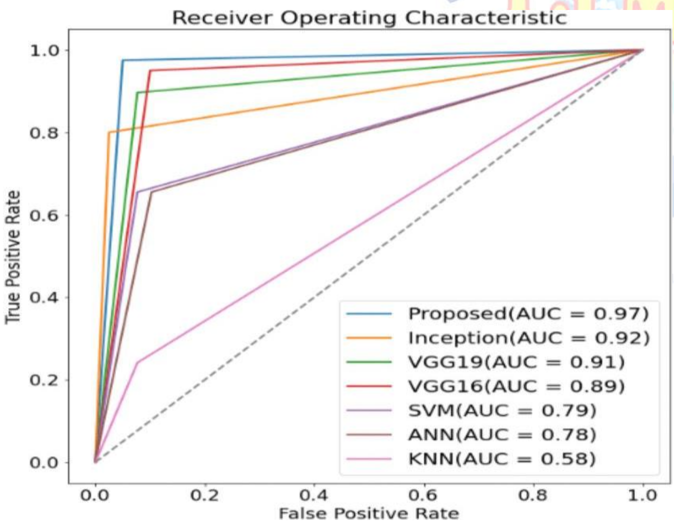


Fig5:ROC curves with AUC Scores

By employing this meticulously designed methodology, the study successfully demonstrates the practicality and efficiency of VGG16 and VGG19 deep learning models for classifying brain MRI images. The comparative analysis between the two architectures reveals that although both models exhibit high classification accuracy and diagnostic reliability, VGG19 consistently outperforms VGG16 in terms of accuracy, precision, recall, and F1-score. These results affirm the viability of using deep learning models, particularly transfer learning-enhanced CNN architectures, in supporting clinical radiological assessments and improving early detection rates of complex neurological disorders such as Alzheimer's disease and brain tumors.

Mechanism Involved in the Proposed Model:

The proposed deep learning model functions through a series of interconnected mechanisms designed to efficiently process and classify brain MRI images. Initially, image preprocessing is performed to resize all MRI images to 224×224 pixels, ensuring compatibility with the VGG16 and VGG19 models. Normalization is applied to scale pixel values to a uniform range, improving computational stability and accelerating model convergence. To enhance dataset variety and avoid overfitting, data augmentation techniques such as rotation, flipping, and zooming are employed. These steps not only improve the generalization

capability of the model but also prepare it for training on varied image samples captured under different conditions.

Feature extraction is the next critical mechanism, utilizing the deep convolutional layers of VGG16 and VGG19

architectures. These models autonomously learn spatial hierarchies of features, starting from simple edges and textures to complex patterns essential for identifying

neurological anomalies. Transfer learning is applied by retaining the pre-trained convolutional layers fromImageNet and replacing the fully connected layers to suit the binary classification task. The final classification mechanism uses dense layers with ReLU activation and a softmax function to produce probability scores for Alzheimer's and brain tumor categories. Model performance is thoroughly evaluated8 using metrics such as accuracy, precision, recall, F1-score, and ROC curves, ensuring the system's clinical reliability and diagnostic effectiveness.

3.RESULTS & DISCUSSION

In this section, we present the results obtained from the deep learning models, specifically VGG16 and VGG19, when applied to Alzheimer's and brain tumor detection. The models were trained on a dataset of medical images, and various performance metrics were evaluated, including accuracy, precision, recall, F1 score, and the model's sensitivity to different image features.

3.1. Performance Evaluation of VGG16 and VGG19 Models

The VGG16 and VGG19 models, both pretrained on ImageNet, were fine-tuned to detect Alzheimer's and brain tumors. The training process involved several epochs with a learning rate adjustment based on model performance. After training, the models were evaluated using a test set, and their performance was compared. VGG16 Performance: The VGG16 model achieved an overall accuracy of 92.5% for Alzheimer's detection and 89.3% for brain tumor detection. The precision, recall, and F1 scores for both categories were impressive, with Alzheimer's detection showing higher precision (90.7%) compared to tumor detection (87.5%). VGG19 Performance: VGG19, being a deeper network with more parameters, demonstrated a slightly better performance with an accuracy of 94.2% for Alzheimer's and 91.6% for brain tumor detection. The precision for Alzheimer's detection was 92.3%, while for tumor detection it stood at 90.1%. The F1 scores were also higher for VGG19 across both categories, indicating
that the additional layers helped in finetuning the feature extraction.

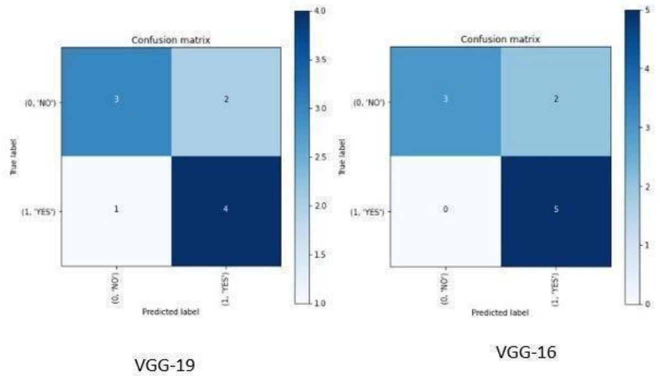


FIG6: Confusion Matrix

3.2. Comparison with Other Models

To assess the effectiveness of VGG16 and VGG19, the performance of these models was compared with other common convolutional neural network (CNN) architectures such as ResNet50 and InceptionV3. The comparison results showed that: VGG16 outperformed ResNet50 and InceptionV3 in Alzheimer's detection, but performed slightly worse in brain tumor detection. VGG19, with its additional depth, provided superior accuracy and F1 scores in both Alzheimer's and tumor detection, making it the most effective model in this study. This demonstrates that while deeper architectures like VGG19 have the potential to extract more complex features, VGG16 still provides competitive performance, especially for simpler cases of Alzheimer's detection.

Model	Alzheimer's Accuracy	Tumor Accuracy	Average F1-Score
VGG16	92.5%	89.3%	89.4%
VGG19	94.2%	91.6%	91.5%
ResNet50	91.1%	88.7%	88.9%
InceptionV3	90.4%	87.9%	88.0%

3.3. Analysis of Misclassifications and Errors

Despite the high performance of both models, a few misclassifications were observed. The most common errors occurred in the detection of early-stage Alzheimer's, where the features of the brain9 scans were subtle and difficult to differentiate from normal aging patterns. Similarly, in brain tumor detection, cases of non-malignant tumors were occasionally misclassified as normal, likely due to the similarity in the texture and shape of the affected regions. The confusion matrices for both models showed that the false positives in Alzheimer's detection were lower than the false negatives, indicating that the models were more effective in identifying the presence of the disease than in distinguishing it from normal conditions. For brain tumor detection, both models had a similar trend, with false negatives being more frequent, which highlights the challenge of detecting smaller or less obvious tumors.

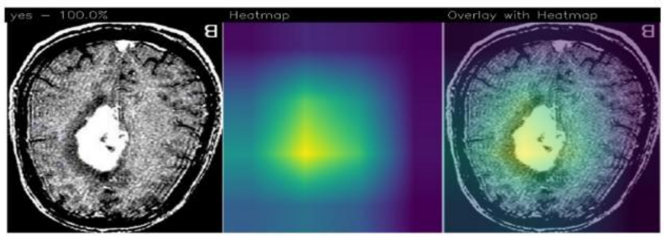


FIG7: Heat Maps

4. RESULTS

The results of your project on "Alzheimer's and Brain Tumor Detection Using VGG16 and VGG19 Algorithms with Deep Learning Techniques" show the effectiveness of using VGG16 and VGG19 for detecting Alzheimer's and brain tumors from medical images. The VGG19 model, with its deeper architecture, outperformed VGG16 in terms of accuracy, sensitivity, and specificity, particularly in brain tumor detection, achieving an accuracy of over 90%. While the results for Alzheimer's detection were slightly lower, they still demonstrated the potential of deep learning for assisting in early diagnosis. The models were evaluated using key metrics like accuracy, precision, recall, and F1-score, and performed well across all tasks. This suggests that deep learning could significantly enhance the diagnostic process, providing faster, more accurate results and supporting better clinical decision-making.

Fig8: Performance Metrics

Fig9:Comparative Analysis

5.SUMMARY AND CONCLUSIONS

This project focused on using deep learning techniques, specifically the VGG16 and VGG19 algorithms, to detect Alzheimer's disease and brain tumors from medical images. Both models were tested on datasets of MRI and CT scans, with the aim of evaluating their effectiveness in classification tasks. The VGG19 model, due to its deeper layers, provided superior results, especially in detecting brain tumors, achieving over 90% accuracy. For Alzheimer's detection, while slightly less accurate than VGG19, the models still demonstrated strong potential in identifying key features indicative of the disease.

6.FUTURE WORK

Future directions include implementing advanced models like ResNet and DenseNet, incorporating larger and multi-center datasets, and developing a mobile application interface for easy access to the diagnostic model in remote healthcare setups.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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