EARLY DETECTION OF ALZHEIMER'S DISEASE USING NEURO IMAGING AND DEEP LEARNING TECHNIQUES

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ABSTRACT

Alzheimer's disease (AD) is a neurodegenerative disorder characterized by progressive cognitive decline and memory impairement. This disease causes the person to suffer from memory loss,unusual behaviour,and language problems.The initial symptoms,such as episodic memory impairement and the navigational problem of the patient, are typical variants. In this project,we propose a deep-learning approach for the early and accurate detection of AD using MRI images.

In the existing system, they used deep learning models such as Convolutional Neural Networks (CNN) and the architecture of LeNet5 to detect the disease.In the proposed system ,we use The Deep Learning Models as a Modified Mobile Net algorithm and classify the images as Mild Demented, Moderate Demented, Non-Demented, or Very Mild Demented.In this study, we are using the ADNI dataset. Using these algorithms may get better accuracy with CNN and Mobile Net compared to the existing system.This can be utilized in the future to classify the types of different classifications easily which is easy to find out the infections in the initial stages and can be cured in the initial stages only.

Keyword: - *Deep Learning, Convolutional Neural Networks (CNN), Mobile-Net*

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1. INTRODUCTION

Alzheimer's disease (AD) represents a major global health challenge characterized by its insidious onset,progressive nature, and profound impact on cognitive function and memory.First elucidated by the seminal work of German psychiatrist Alois Alzheimer in 1906, AD predominantly affects older adults, initially showing mild cognitive impairment that escalates over time. As the disease progresses, individuals experience severe problems with memory retention, problem-solving, decision-making, and language skills, ultimately leading to a profound decline in quality of life. The urgency of early detection and intervention in AD cannot be overstated. Early diagnosis facilitates rapid access to treatment and support services, enabling individuals and their families to better manage disease progression and optimize patient outcomes. However, traditional diagnostic methods often rely on clinical assessment and cognitive tests, which can be subjective prone to variability.In recent years,advances in medical imaging and machine learning have revolutionized AD diagnostics,offering new approaches to detect subtle brain abnormalities indicative of the disease.

Deep learning, a subfield of machine learning, has proven to be a powerful tool for analyzingmedical imaging data and extracting meaningful insights.(CNNs) Convolutional neural networks have shown remarkable effectiveness in identifying patterns and features in MRI images that correlate with AD pathology. Using these advanced computing techniques,researchers have sought to develop automated systems capable of accurately classifying AD severity and predicting disease progression. We present a comprehensive review of the current state of the art in deep learning-based approaches to AD detection and classification.We highlight recent advances in CNN architecture, including the use of lightweight models such as Mobile-Net, which offer increased computational efficiency without compromising accuracy. In addition, we discuss the critical role of large-scale datasets such as Alzheimer's Disease Neuroimaging Initiative (ADNI) in training and validating deep learning models for AD Diagnosis.

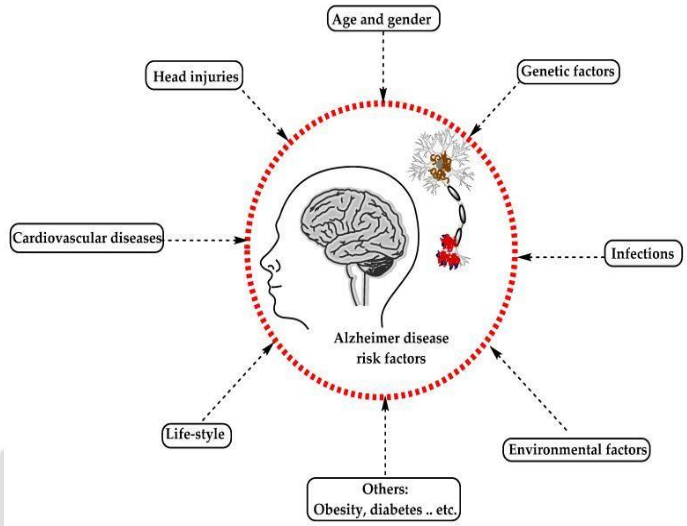

Fig 1: Alzheimer Disease Risk Factor

Our study aims to contribute to ongoing efforts to improve the early detection and classification of AD through MRI image analysis. By evaluating the performance of state-of the-art deep learning models on real-world datasets, we aim to identify the most effective methodologies for accurately stratifying AD severity and predicting disease progression. We further explore the potential implications of our findings for clinical practice, including the development of automated diagnostic tools and personalized treatment strategies. we strive to advance the field of neuroimaging and contribute to the development of innovative solutions for the early diagnosis and treatment of AD. By harnessing the power of deep learning and medical imaging analytics, we aim to provide healthcare professionals with the tools and insights needed to effectively combat this devastating neurodegenerative disorder.

2. LITERATURE SURVEY

Alzheimer's disease (AD) detection and classification have been the subject of extensive research, with notable contributions from various studies:

• [SUHAD AL-SHOUKRY et al., 2020] conducted a mini-review on Alzheimer's disease detection using deep learning algorithms. They emphasized the importance of accurate diagnosis, particularly in the early stages of the disease. The review highlighted the role of Deep Learning (DL) in enabling early diagnosis and explored relevant literature in this area.

• [Ruoxuan Cui et al., 2019] Proposed a method for hippocampus analysis in Alzheimer's disease diagnosis. Their approach combines 3-D Dense Net and shape analysis to analyze the hippocampus region, a crucial area affected by AD. The method demonstrated high classification accuracy and outperformed existing techniques.

• [IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)] The symposium presented an efficient 3D convolutional network (3D Convent) architecture for automatic extraction of features from MRI brain scans and Alzheimer's Disease (AD) diagnosis. The proposed method achieved high performance in AD detection on a relatively large dataset, showcasing its effectiveness in early diagnosis.

• [TIAGO CARNEIRO et al., 2018] evaluated the performance of Google Collaboratory as a tool for accelerating deep learning applications, including those related to AD diagnosis. Their analysis focused on hardware resources, performance, and limitations of Collab, providing insights into its suitability for AD-related research.

3. METHODOLOGY

1. Data Collection and Preprocessing: To ensure a representative and diverse sample, we obtain MRI images from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. To improve the quality and uniformity of the images, preprocessing techniques like noise reduction, resizing, and normalization are applied.

2. Model Selection and Architecture: The Mobile-Net architecture is used because of its effective image classification performance and lightweight design. Mobile-Net is ideally suited for our application since it provides the benefit of quicker inference times without sacrificing accuracy.

3. Training and Validation: Using supervised learning, the chosen Mobile-Net model is trained on the preprocessed MRI images. To assess the model's performance and avoid overfitting, we divided the dataset into training and validation sets. Back propagation is used to optimize the model's parameters during training.

4. Classification: Once the model is trained, we perform classification on unseen MRI images to predict the presence and severity of Alzheimer's disease. The model categorizes the images into specific classes, including Mild Demented, Moderate Demented, Non-Demented, or Very Mild Demented based on the patterns and features learned during training like:

Brain Atrophy (loss of brain tissues)
Enlarged ventricles (fluid-filled spaces b/w neurons),
Cortical thinning (causes the thickness of the cerebral cortex),
White matter Lesions (disruption in neural connections) confirms the presence of Alzheimer’s disease.

5. Evaluation: We use several metrics, including accuracy, precision, recall, and F1 score, to assess how well the trained model performs. Furthermore, we examine confusion matrices to evaluate the model's accuracy in classifying Alzheimer's disease at various stages.

6. Fine-tuning and Optimization: We may investigate methods like hyperparameter tuning and transfer learning to further enhance the model's performance. Optimizing techniques help improve the model's robustness and generalization, while fine-tuning enables us to tailor pre trained models to our dataset.

7. Deployment and Integration: After the trained model performs well, we integrate it into an intuitive application or user interface. With the help of this interface, medical professionals can quickly and automatically diagnose patients with MRI images, allowing for the early identification and treatment of Alzheimer's patients.

4. PROPOSED SYSTEM ARCHITECTURE

In the proposed system the purpose of our project is to utilize deep learning techniques for the early and accurate classification of Alzheimer's Disease (AD) through the analysis of MRI images.We have used Mobile Net Architecture to enhance better results.It is used to classify MRI images (or) AD images into specific categories, such as Mild, Moderate, No-AD or High.It might create a foundation for future applications by proposing a system that can be easily extended to classify different types and encourage early intervention in various medical conditions.It aims to reduce the complexity of the classification system while maintaining or improving accuracy.Identifying the disease in its early stages by performing early diagnosis. We perform classification based on the features extracted from the MRI Images of different patients, using proposed deep learning algorithms.

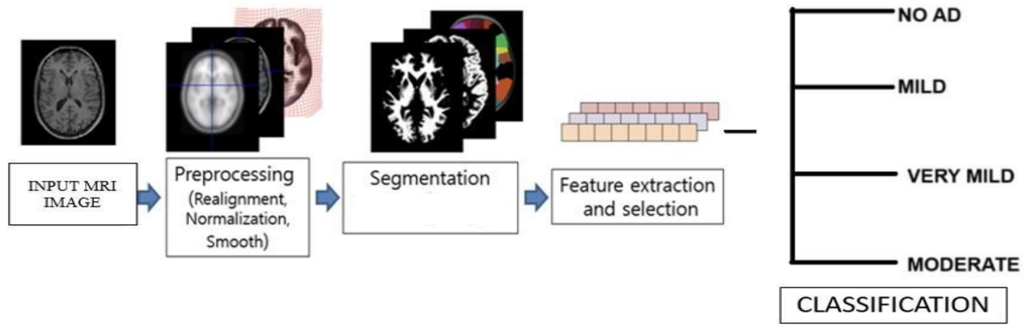

Fig 3: Proposed System Architecture diagram for Alzheimer's disease classification.

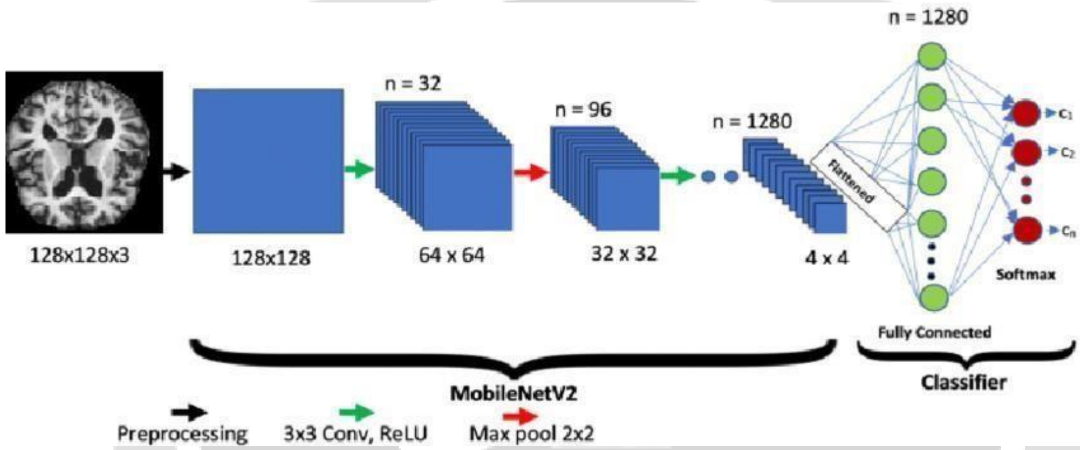

Fig 4: Architecture of MobileNetV2 implemented in this project

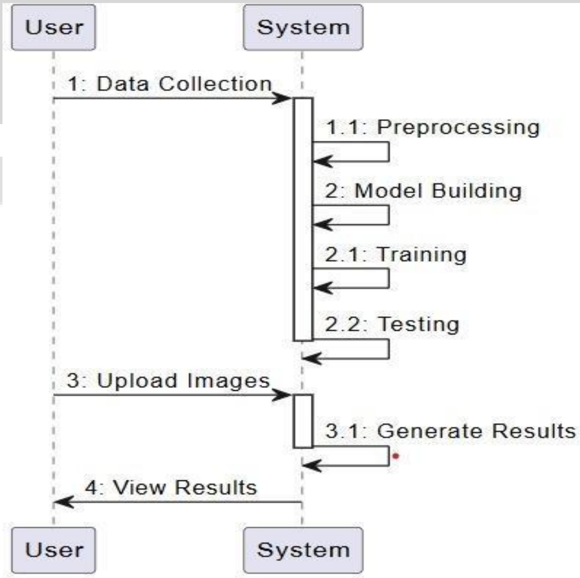

Fig 5: Sequence Diagra

5. DATASET

Alzheimer's disease detection using deep learning algorithms and MRI image analysis yielded promising results, demonstrating the effectiveness of our proposed methodology.

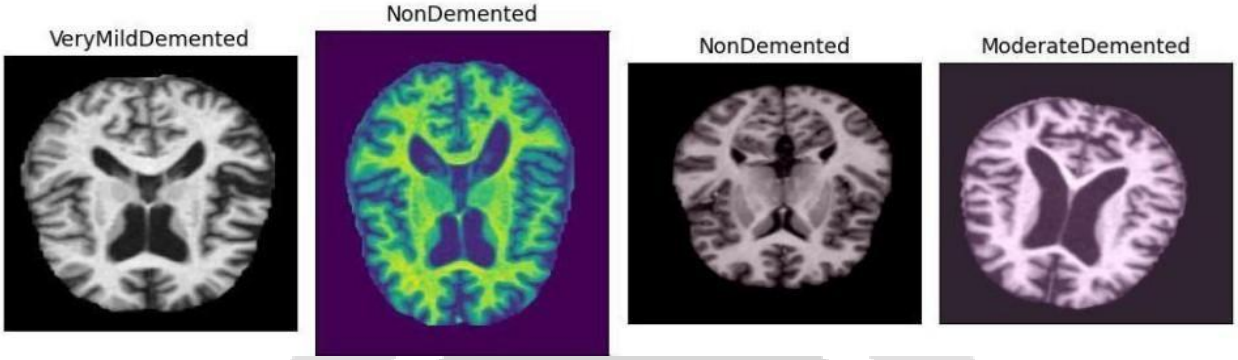

Fig 6: Displaying some random MRI images classified into respective classes from the ADNI Data set.

6. RESULTS

Predicted Images corresponding to their respective severity levels are as follows: (Mild, Moderate, No-AD, Very Mild)

Fig 7: Mild Demented

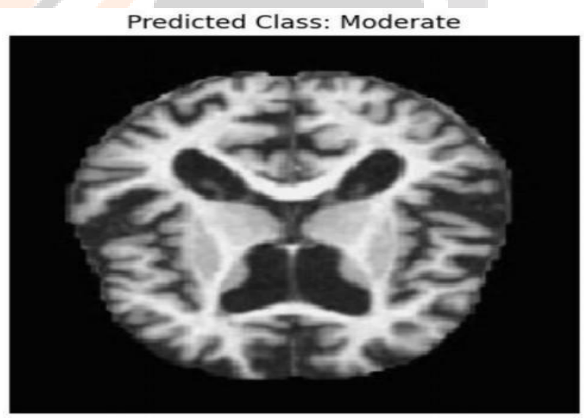

Fig 8:Moderate Demented

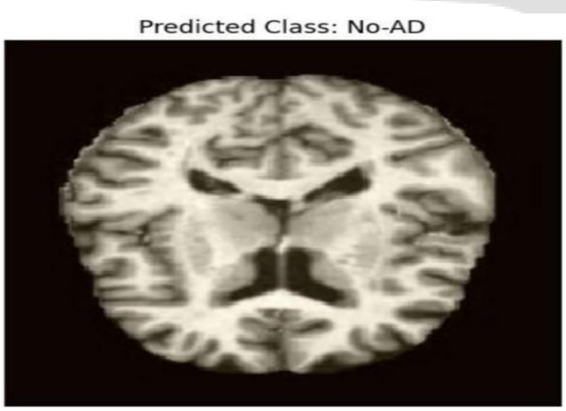

Fig 9: No-AD

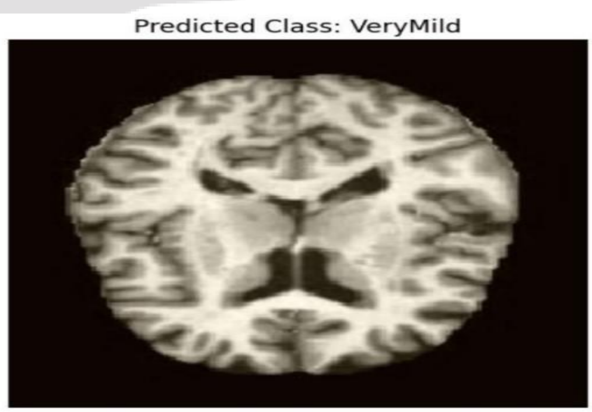

Fig 10: Very Mild

7. RESULT ANALYSIS:

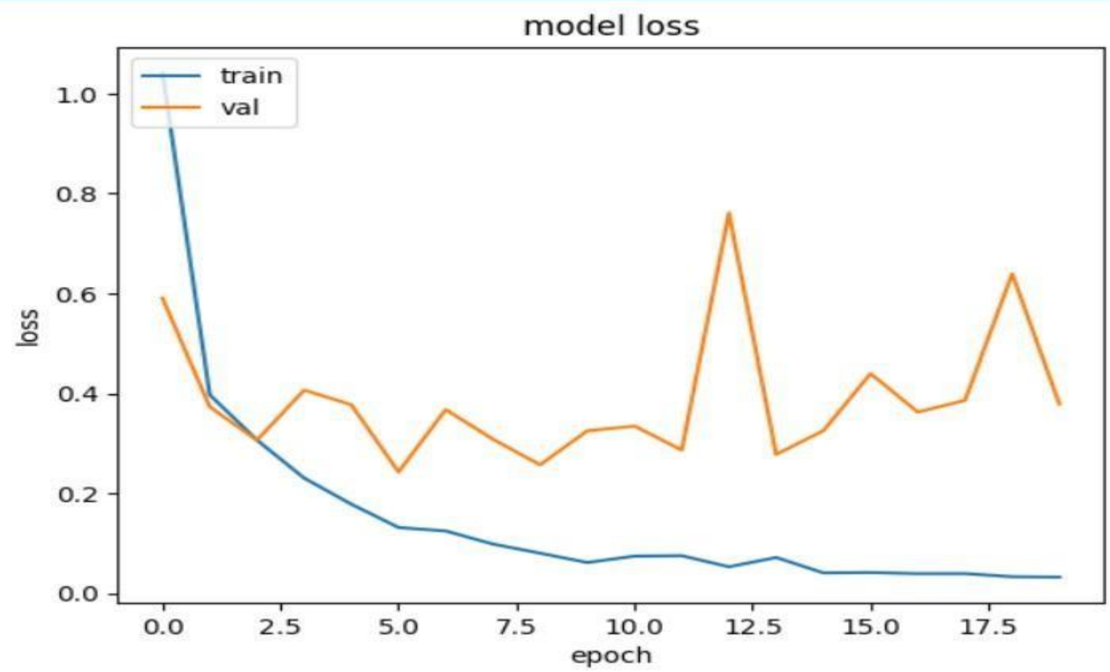

Fig 11: Graphical representation of the Model Loss

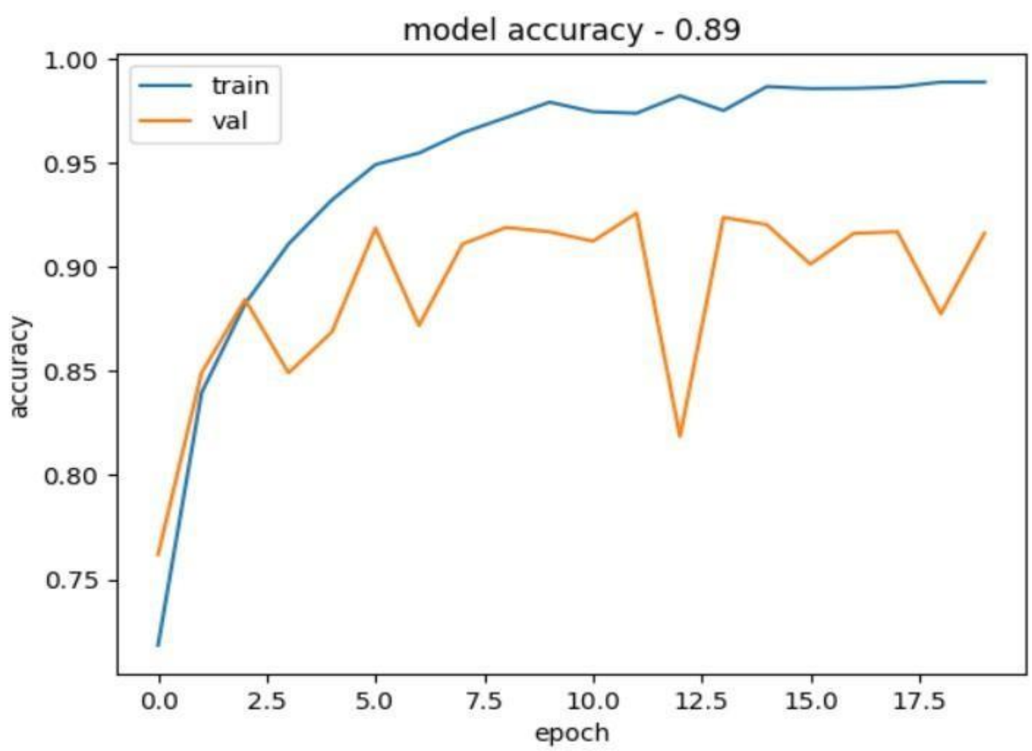

Fig 12: Graphical representation of the Model Accuracy

Result Analysis of the Model

The given images represent the performance evaluation of a machine learning model, visualized through two key metrics: accuracy and loss over epochs for both training and validation datasets. Let's dive into the detailed breakdown and interpretation of the results.

1. Model Accuracy Analysis

The first plot depicts model accuracy over 19 epochs, with separate lines for training accuracy (blue) and validation accuracy (orange). Accuracy measures the proportion of correct predictions out of total predictions, making it a crucial metric in classification problems.

Early Phase (Epoch 0-3):

The model shows a rapid increase in both training and validation accuracy. Initially, the training accuracy starts lower than validation but quickly surpasses it, which is expected because the model learns patterns from the training data faster.

Mid Phase (Epoch 4-10):

The training accuracy continues improving steadily, reaching around 95%, while validation accuracy fluctuates between 85% and 90%. This fluctuation suggests the model is generalizing to unseen data but also hints at potential overfitting.

Late Phase (Epoch 11-19):

Training accuracy plateaus near 99%, indicating the model has almost perfectly memorized the training data. However, validation accuracy stays inconsistent, with occasional sharp dips (notably around epoch 12), a sign of overfitting — where the model performs well on training data but struggles with validation data. The final accuracy value of 0.89 (89%) for validation is reasonably good, but the divergence between the two curves suggests room for improvement.

2. Model Loss Analysis

The second plot illustrates model loss over epochs for both training (blue) and validation (orange) data sets. Loss quantifies how poorly the model's predictions match the actual labels - lower loss implies a better model.

Early Phase (Epoch 0-3):

The training loss starts high (1.0) and drops rapidly, showing the model quickly learns basic patterns. Validation loss follows a similar decline initially but stabilizes at a higher value.

Mid Phase (Epoch 4-10):

Training loss keeps reducing smoothly, reaching near 0.1. Validation loss, however, fluctuates around 0.3-0.4, indicating the model isn't learning as effectively for unseen data. This behavior supports the accuracy chart's observation of validation inconsistencies.

Late Phase (Epoch 11-19):

Training loss remains minimal (close to 0), signaling the model is highly confident on the training set. However, validation loss becomes erratic, spiking at several points, like epoch 12 and epoch 17, highlighting overfitting. The model memorizes training data too well, losing flexibility to handle new data.

Confusion Matrix:

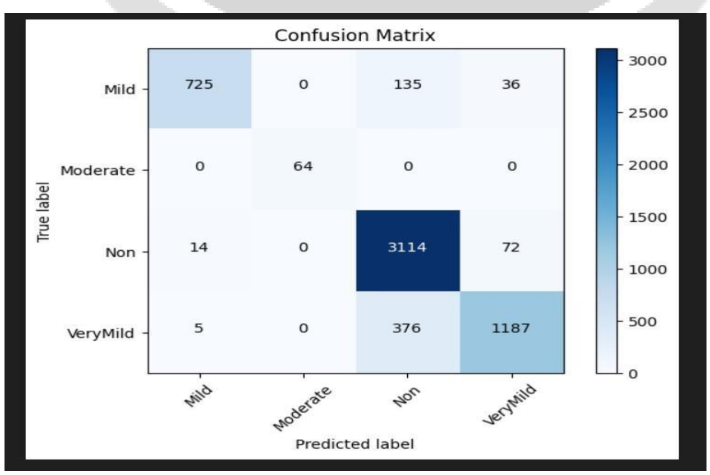

Fig 13: Confusion Matrix

Introduction to the Confusion Matrix:
A confusion matrix is a performance evaluation tool that visualizes how well a classification model performs. It compares the true class labels with the predicted class labels, providing abreakdown of correct and incorrect classifications. This matrix is particularly useful in multi class classification problems, such as the one displayed here.In this specific confusion matrix, we observe four classes:Mild,Moderate,Non,VeryMild.

Matrix Breakdown

True Label → Predicted Label	Mild	Moderate	Non	VeryMild
Mild	725	0	135	36
Moderate	0	64	0	0
Non	14	0	3114	72
VeryMild	5	0	376	1187

Key Interpretation:
Diagonal values (True Positives): These are the successful predictions — where the model correctly labeled the data.
Off-diagonal values (False Positives/Negatives): These are the errors — cases where the model predicted a different class than the actual one.
Performance Insights and Observations
1. **Mild Class Performance:**
Correctly classified: 725 cases.
Misclassified as "Non": 135 times — quite significant.
Misclassified as "Very Mild": 36 times — less frequent but still noteworthy.
The model seems to confuse Mild with Non, suggesting overlapping features between these two classes.
2. **Moderate Class Performance:**
64 correct classifications and 0 misclassifications — this is a perfect performance for this class, indicating clear separation between Moderate and other classes. This implies that the Moderate class has distinctive features that the model can easily differentiate from the others.
3. **Non Class Performance:**
3114 correct classifications - the darkest cell on the matrix, representing the majority class. 14 cases misclassified as Mild and 72 cases misclassified as VeryMild — these numbers are relatively small compared to the total, showing strong performance on this class.However, the model confuses Non and VeryMild more than other combinations.
4. **VeryMild Class Performance:**
1187 correct classifications, but 376 cases misclassified as Non — a significant error rate. This may suggest feature similarity between Very Mild and Non, leading to misclassification.
5. cases wrongly classified as Mild — though small, this error might indicate slight feature overlap or noise in the dataset.

8. CONCLUSION

Alzheimer's disease (AD) poses a significant challenge to global health care due to its progressive nature and devastating impact on cognitive functions. Our project employs state of-the-art deep learning techniques, particularly the Mobile-Net architecture, to address the early and accurate classification of AD using MRI images. By leveraging the ADNI dataset, we have demonstrated promising results in classifying MRI images into specific categories, including Mild Demented, Moderate Demented, Non Demented, or Very Mild Demented. This underscores the potential of deep learning to improve the early detection and management of AD, ultimately advancing health care technology and patient care. Our study underscores the potential of deep learning algorithms in enhancing the accuracy and efficiency of AD diagnosis, enabling early intervention and treatment. By paving the way for future applications in medical imaging analysis, our project contributes to advancing health care technology.

9. FUTURE WORK

In our future research, we aim to explore more advanced deep-learning methods to better understand Alzheimer's disease. We will investigate using different types of neural networks to analyze MRI data over time, helping us spot changes in the brain more accurately. We also plan to combine MRI with other medical tests to improve diagnosis. Additionally, we will adapt our model to work with different groups of people and health care settings. By making our predictions easier to understand, we hope to collaborate closely with doctors to ensure our research benefits patients directly.

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