Cognitive Care: A Comprehensive Detection and Management of Alzheimer's Disease

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Abstract— **This study proposes an innovative approach to tackle Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) by combining medical expertise with modern technology. Through the integration of Health Expertise and Machine Learning (ML), we aim to create a robust software platform for early detection and improved patient recovery. Our method involves analyzing neurological data to uncover patterns crucial for informed decision-making in managing AD and MCI. Additionally, our software incorporates cognitive games tailored for Alzheimer's patients to enhance cognitive functions and engagement, along with a community forum designed for support and shared experiences. Furthermore, we utilize a Convolutional Neural Network (CNN) model for efficient classification of AD, ensuring accurate diagnosis. This research promises to reshape the landscape of cognitive disorder diagnosis and treatment, offering hope for better outcomes for patients and their families.**

Keywords— **Alzheimer's Disease, Detection, Dementia, Machine Learning, Cognitive, CNN, Tensor Flow, Keras, Scikit Learn, Remedies.**

I. Introduction

Alzheimer's disease (AD) presents a pressing global health challenge, with its prevalence expected to rise in the coming years. Early detection and management of AD are crucial for improving patient outcomes and alleviating the burden on caregivers and healthcare systems. However, current diagnostic methods face limitations, including the reliance on manual interpretation of MRI images and the lack of comprehensive tools for disease management. To address these challenges, this research paper proposes a holistic approach to AD detection and management. Leveraging deep learning techniques, particularly Convolutional Neural Networks (CNNs), our study focuses on automating the classification of brain MRI images into various disease classes. Building upon existing literature, we aim to improve diagnostic accuracy by integrating deep learning algorithms. In addition to disease detection, our project aims to enhance patient care and support for caregivers through the implementation of cognitive games, an appointment booking system with doctors, and a robust community platform. By providing a comprehensive solution that encompasses early detection, personalized care, and community support, we seek to contribute to the advancement of Alzheimer's disease research and healthcare. Through this research, we hope to address key challenges in AD detection and management. By this we aim to pave the way for more accurate and comprehensive approaches to Alzheimer's disease detection and management.

II. Literature Survey of Existing Systems

In the study by M. Talo et al. [1], the focus is on addressing the challenges associated with manual diagnosis of brain disorders using MRI images. The researchers employ deep learning models, to automatically classify MRI images into various disease classes. ResNet-50 is identified as the most accurate model, achieving a classification accuracy of 95.23% ± 0.6 [1]. The study underscores the potential of this model for testing with a large dataset of MRI images, offering clinicians a valuable tool for validating their findings after manual examination.

In a different context, El Sappagh et al. [2] explores the prediction of Alzheimer's disease (AD) progression over 2.5 years. The research stands out for incorporating time-series features such as patient comorbidities, cognitive scores, medication history, and demographics, along with the semantic preparation of medication and comorbidity text data. The study compares five machine learning algorithms, highlighting the random forest model's superior performance [2]. Notably, this work represents the first of its kind to delve into the role of multimodal time-series data in AD prediction.

De, A et al. [3] introduced a novel approach for automating the classification of Alzheimer's disease using 3D Diffusion Tensor Imaging (DTI) data. The paper employs Convolutional Neural Networks (CNNs) and a Random Forest Classifier

(RFC) separately, achieving a high classification accuracy of 92.6% [3].

In the study by M. Rohanian et al. [4], the authors contribute to the ADReSS challenge, focusing on predicting the severity of Alzheimer's Disease using speech data. The paper explores acoustic and natural language features in spontaneous speech and their correlation with Alzheimer's diagnosis and mini-mental state examination (MMSE) score prediction. The proposed model utilizes separate Long Short-Term Memory (LSTM) networks for text and audio data, combining their outputs with a gating mechanism for the final prediction [4].

Moving from the realm of speech analysis to neuroimaging, Zheng, X et al.[5] employs a statistical likelihood-ratio approach for computer-assisted diagnosis in Alzheimer's disease. This innovative method relies on signal detection theory and utilizes medial temporal lobe (MTL) volumes derived from T1-weighted MRI images. The study showcases the tool's effectiveness, achieving notable sensitivity and specificity for the Minimal Interval Resonance Imaging in Alzheimer's Disease (MIRIAD) dataset[5]. Transitioning further, Shukla, A et al.[6] provides a comprehensive review on Alzheimer disease detection methods, shifting the focus towards automatic pipelines and machine learning techniques. The paper discusses various approaches, including Biomarker Methods, Fusion, and Registration for multimodality, in pre-processing medical scans. While acknowledging the success of automated pipelines in single and binary class classifications, the study also recognizes the challenges in multi-class classification, emphasizing the importance of multi-modality approaches for effective validation [6].

Afzal et al. [7] review classification frameworks utilizing MRI, fMRI, PET, and amyloid-PET scans, highlighting the effectiveness of deep learning and Support Vector Machine classifiers.Goenka and Tiwari [8] emphasize the importance of considering multiple modalities of neuroimaging biomarkers for accurate AD classification and highlight the potential of deep learning models in predicting AD based on brain biomarkers.Salehi et al. [9] implement a CNN for early AD diagnosis using MRI images, showcasing its potential. Yet, relying solely on MRI images may limit the model's effectiveness.Basaia et al. [10] focus on CNNs for automated AD and Mild Cognitive Impairment (MCI) detection from MRI scans, demonstrating high accuracy in distinguishing patients from healthy controls. However, they acknowledge the need for further research to incorporate additional biomarkers and enhance real-world performance.

Bandyopadhyay et al. [11] propose a method utilizing ensemble learning and artificial neural networks (ANN) on the OASIS dataset. They compare the performance of different machine learning algorithms and ANNs in AD detection. Feng et al. [13] introduce an automated approach for AD diagnosis using Diffusion Tensor Imaging (DTI) in 3D, achieving a classification accuracy of 92.6%. This is accomplished through the combination of Convolutional Neural Networks (CNNs) and a Random Forest Classifier (RFC). Basaia and Agosta [14] focus on CNNs for automated AD and Mild Cognitive Impairment (MCI) detection from MRI scans, demonstrating high accuracy in distinguishing patients from healthy controls. Maringanti et al. [12] also discuss machine learning and deep learning models for early-stage AD detection, providing insights into the complexities and computational costs associated with such approaches.

Common shortcomings across these papers include limited data availability, complexities in feature extraction, computational costs, and the necessity for further research to enhance real-world applicability and performance.

III. Limitations In Existing System

The challenges in Alzheimer's disease detection research are multifaceted. Firstly, there is a scarcity of publicly available large datasets for research, limiting the availability of labeled datasets and subsequently affecting model accuracy and study comprehensiveness. Additionally, the issue of class imbalance, with variations in the number of samples across different classes (AD, MCI, normal), can significantly impact the performance of machine learning algorithms. The lack of detailed model information, encompassing architecture, training procedures, and hyperparameter settings, impedes transparency and replicability. The restricted use of fusion techniques for combining information from various sources further hampers performance, as does the overemphasis on a single biomarker, such as medial temporal lobe atrophy (MTA), at the expense of integrating other valuable biomarkers like cerebrospinal fluid analysis (CSF) and Positron Emission Tomography (PET) imaging. Quality concerns related to poor image quality during pre-processing pose a risk to the accuracy of Alzheimer's disease detection. Additionally, the omission of influential factors, including gender, brain size, and age corrections in brain volume calculations, could impact diagnostic accuracy. Lastly, the lack of clarity in some proposed frameworks, with insufficient explanations, makes it challenging for others to replicate results and advance the field.

IV. Proposed System

The objective of our project is to develop a comprehensive application for Alzheimer's disease (AD) detection and management. This application will integrate several key features to enhance early detection, cognitive assessment, caregiver support, and overall patient care

1. Alzheimer's Disease Detection: The implementation of a CNN model for classification of brain MRI images is crucial for early detection of AD. Early detection allows for timely intervention and treatment, which can significantly improve patient outcomes and quality of life. This feature is essential for improving diagnostic accuracy and facilitating early intervention strategies.
2. Mini-Mental State Examination (MMSE) Integration: The integration of the MMSE test allows for regular cognitive assessment, providing healthcare providers with valuable insights into the progression of AD. Monitoring cognitive function over time can help healthcare providers tailor treatment plans and interventions to individual patient needs.

This feature is important for tracking disease progression and optimizing patient care.
3. Cognitive Games: Cognitive games are designed to help maintain and improve cognitive function in AD patients. These games can be engaging and enjoyable, encouraging regular use and providing a fun way to stimulate cognitive abilities. Cognitive stimulation has been shown to have positive effects on cognitive function in AD patients, making this feature an important component of our project.
4. Appointment Booking System: The appointment booking system allows AD patients and their caregivers to easily schedule appointments with healthcare providers. This feature streamlines the process of seeking medical help, ensuring timely access to healthcare services. As timely access to healthcare is crucial for managing AD and addressing any emerging health issues promptly.
5. Caregiver Support: The caregiver support feature provides a community platform for caregivers to connect, share experiences, and access resources. Caregivers play a crucial role in supporting AD patients, and this feature helps them navigate the challenges of caregiving more effectively. Providing support for caregivers is essential for improving the overall quality of care for AD patients.
6. User-Friendly Interface: Designing the application with a user-friendly interface is essential for ensuring that it is easy to navigate and accessible to users with varying levels of technological proficiency. A user-friendly interface enhances the overall user experience, making it more likely that users will engage with and benefit from the application.

V. Project Architecture

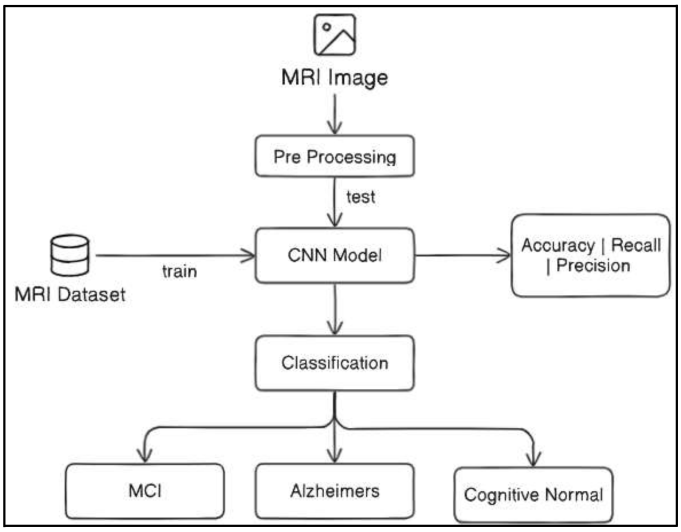

Figure 1: Proposed Architecture

The project architecture , As represented in Fig.1 revolves around a Convolutional Neural Network (CNN) model designed to analyze Magnetic Resonance Imaging (MRI) scans for the purpose of detecting Alzheimer's disease (AD). The system takes an MRI dataset as input, which includes scans from individuals diagnosed with AD, Mild Cognitive Impairment (MCI), and those who are cognitively normal. Before feeding the scans into the CNN model, a pre-processing stage is crucial. Here, techniques like normalization and segmentation ensure the images are standardized and formatted for optimal analysis by the CNN model.

The pre-processed scans are then fed into the CNN model, which is a deep learning algorithm adept at image analysis. This model is designed to extract features from the MRI scans that are indicative of AD. To achieve this, the CNN model undergoes a training phase where it is presented with MRI scans and their corresponding labels (AD, MCI, or cognitively normal). Through this training, the model learns to identify patterns in the scans that are associated with each label.

Once trained, the model's performance is evaluated on a separate testing set, which consists of MRI scans the model has not encountered before. Metrics like accuracy, recall, and precision are used to assess the model's effectiveness. Finally, the trained and evaluated model can be employed to classify new MRI scans, providing an output classification of AD, MCI, or cognitively normal.

VI. Implementation

A] Alzheimer's Detection using Convolutional Neural Network Model :

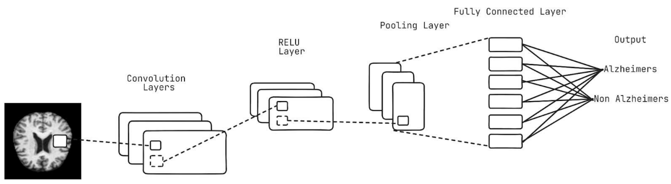

Figure 2: Visualization of CNN Model.

In our project, we implemented a Convolutional Neural Network (CNN) for the detection of Alzheimer's disease using medical imaging data. The CNN was designed to process 2D images with dimensions of 150x150 pixels and three color channels. To enhance the model's generalization capabilities and robustness, we employed data augmentation techniques during training. The ImageDataGenerator from the Keras library was utilized to perform real-time data augmentation, including rotation, width and height shifts, shear, zoom, and horizontal flips. The dataset was split into training and validation sets using a validation split of 20%.

The CNN architecture comprises three convolutional layers with increasing filter sizes (32, 64, 128), each followed by max-pooling layers to downsample the spatial dimensions. Rectified Linear Unit (ReLU) activation functions were used to introduce non-linearity. Following the convolutional layers, a flattening operation was applied, and two fully connected layers were incorporated for feature extraction and classification. The first dense layer consists of 128 neurons with ReLU activation, followed by a dropout layer with a dropout rate of 0.5 to mitigate overfitting. The final dense layer contains a single neuron with a sigmoid activation function for binary classification (Alzheimer's or non-Alzheimer's).

This CNN-based approach demonstrates promising results in Alzheimer's disease detection, showcasing the potential of deep learning techniques in medical image analysis. Further investigations, refinements in model architecture, and exploration of additional data sources could contribute to enhancing the accuracy and reliability of the proposed model for practical clinical applications.

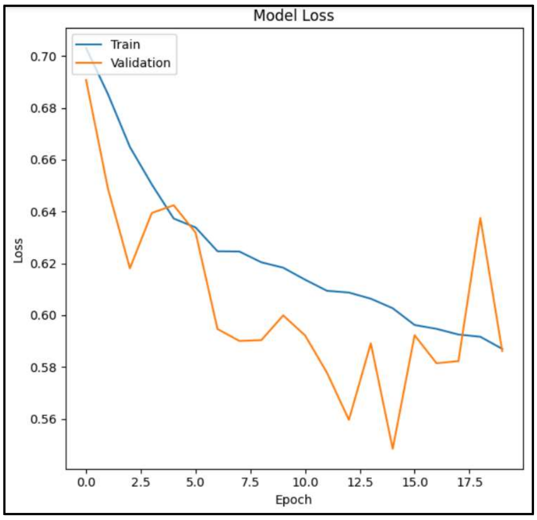

Figure 3a: Epoch vs Loss Line Chart

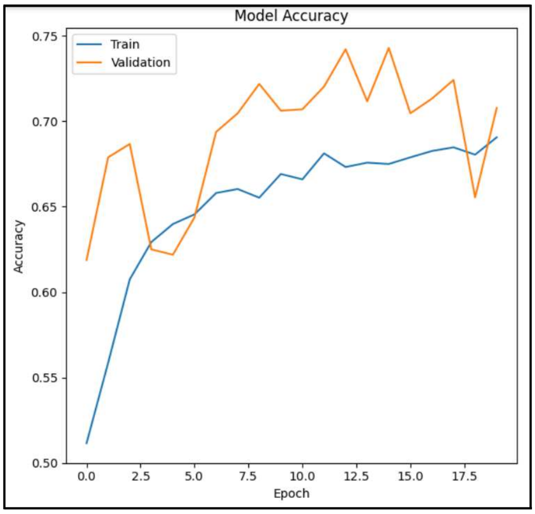

Figure 3b: Epoch vs Accuracy Line Chart

The model was compiled using the Adam optimizer and binary cross entropy as the loss function, while accuracy was chosen as the evaluation metric. The training process was conducted over 30 epochs, and the model's performance was assessed using a separate validation dataset. The achieved accuracy on the validation set was recorded at 70.78%,as represented in Fig 3b, indicating the model's ability to correctly classify Alzheimer's disease based on the provided medical images.

B] Alzheimer's Classification using Transfer Learning Model :

1. Preparing a Dataset:

First, the dataset is divided into train and test sets. Mildly demented, moderately demented, non-demented, and extremely mildly demented are the four categories. An MRI scan of one of these types is represented by each image in the data. The data seems unbalanced, though. Compared to non-demented and very mildly demented, mild and moderately demented individuals have notably less samples. There are 179 mildly demented, 12 moderately demented, 640 non-demented, and 448 very mildly demented people in the test results. There are 717 mildly demented, 52 moderately demented, 2560 non-demented, and 1792 extremely mildly demented people in the train data. According to my high-level examination, the size and positioning of each image appear to be consistent.

2. Using the Inception V3 Model:

A basic model with a single dense layer for classification was trained using DenseNet121, InceptionV3, Xception, and ResNet101 in order to choose a basis model for transfer learning. The AUC for the training set was computed after all pre-trained weights were frozen. There are imbalanced examples of different classes in the image collection. Since accuracy would be skewed towards the highest frequency class, alternative model performance metrics such as AUC were chosen. InceptionV3 had the highest AUC on the test dataset and was selected as the base model (only InceptionV3 is shown for brevity). A number of additional steps were taken to improve the test AUC.

On the ImageNet dataset, the image recognition model Inception v3 has demonstrated accuracy levels of above 78.1%. The model is the result of numerous concepts that have been developed over time by various researchers. The original study "Rethinking the Inception Architecture for Computer Vision" by Szegedy et al. [15] served as its foundation.

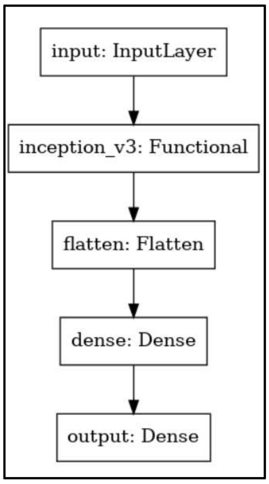

Figure 4: Architecture of Inception V3

The model consists of convolutions, average pooling, max pooling, concatenations, dropouts, and fully linked layers, among other symmetric and asymmetric building pieces. The model makes considerable use of batch normalisation, which is applied to activation inputs. Softmax is used to compute the loss.

The InceptionV3 model is fairly complicated. The general structure, as represented in Fig 4, will stay the same throughout this project discounting some frozen/unfrozen layers and maybe a Dense layer with some regularization. The output layer predicts the four previously mentioned classes and uses the softmax activation function. When compiling the model I use the adam optimizer, categorical cross entropy loss, and AUC as a metric. The model is fitted on the train data and validated on the validation data. Early stopping is being used which monitors the validation AUC.

3. Preprocessing the Image:

We've set the image size to 176x208 pixels and the batch size to 32. Utilizing the ImageDataGenerator class, we normalize the pixel values of the images to a range between 0 and 1, a common preprocessing step in neural network training.We've created three separate generators for training, validation, and test datasets. These generators, employing the flow_from_directory method, read images from specified directories (DIR_TRAIN, DIR_VAL, and DIR_TEST) and organize them into batches during training. The target size of the images is set, and the color mode is configured to RGB.For each set (training, validation, and test), our generators are set up to handle categorical labels, signifying multiple classes in the data. The number of classes is automatically inferred from subdirectories within the specified directories. To ensure reproducibility, we've fixed the random seed for data augmentation using the seed parameter.

4. Data Augmentation:

Data augmentation techniques were applied to the training images to enhance the diversity of the training dataset and improve the robustness of the convolutional neural network (CNN) during training. The ImageDataGenerator is utilized with various augmentation parameters:

- Rotation Range: Images are randomly rotated by up to 5 degrees, introducing variability in orientation to make the model more resilient to different angles of the input data.
- Zoom Range: Random zooming of up to 10% is applied to the images, providing the model with a range of perspectives and scales for improved generalization.
- Width Shift Range and Height Shift Range: Horizontal and vertical shifts of up to 5% are applied, introducing slight translations to the images. This helps the model learn to recognize objects even when their positions vary within the image.

5. Hyperparameter Search using Keras Tuner:

The best hyperparameters for dropout rate, learning rate, and filter size for the convolution and dense layers were found using the keras tuner package. The model with the best performance was generated using the obtained parameters.

- dropout rates: 0.50, 0.60
- learning rate: 1e-3
- convolution layer:1024
- dense layer:1024

6. Base Model(inceptionV3) Training with Optimised Parameters and Data Augmentation:

The number of epochs (set to 50), early termination conditions based on the validation area under the curve (AUC) metric, and a learning rate reduction technique utilising the ReduceLROnPlateau callback were all defined as part of the training parameters, as represented in Fig 5a and 5b. Additionally AUC was chosen as the evaluation metric.

The training process began by loading the InceptionV3 pre-trained model, which served as the base architecture. The layers of the pre-trained model were frozen for training, and a new model was constructed and compiled with optimized hyperparameters such as dropout rate, number of convolutional nodes, dense nodes, and learning rate.

The model was then trained on the augmented training data for the specified number of epochs. During training, the specified callbacks are invoked, including learning rate reduction. The training history, containing information about training and validation performance over epochs, were stored in the history variable.

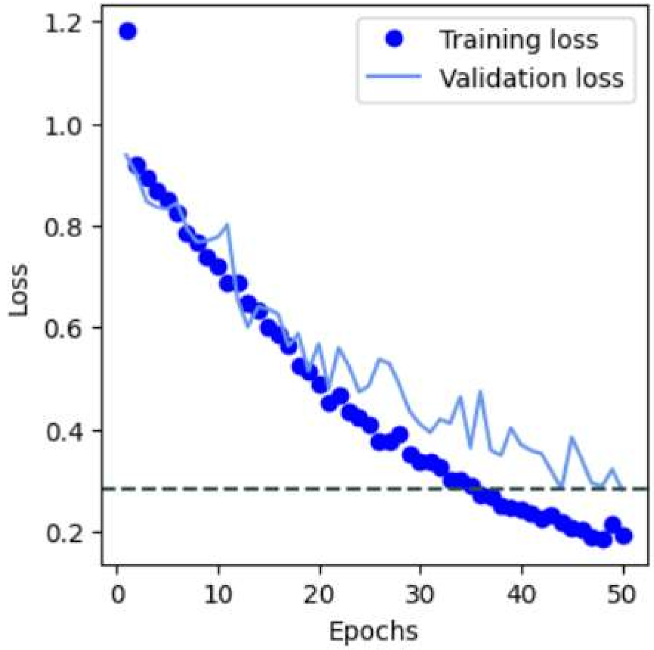

Figure 5a: Validation Loss by Epochs

After training ,we received the model AUC on the test data equal to 88.0%, as represented in Fig 5b. This accuracy can be increased by training the model on more epochs with a lower learning rate so as to give the model as much time to train without overfitting.

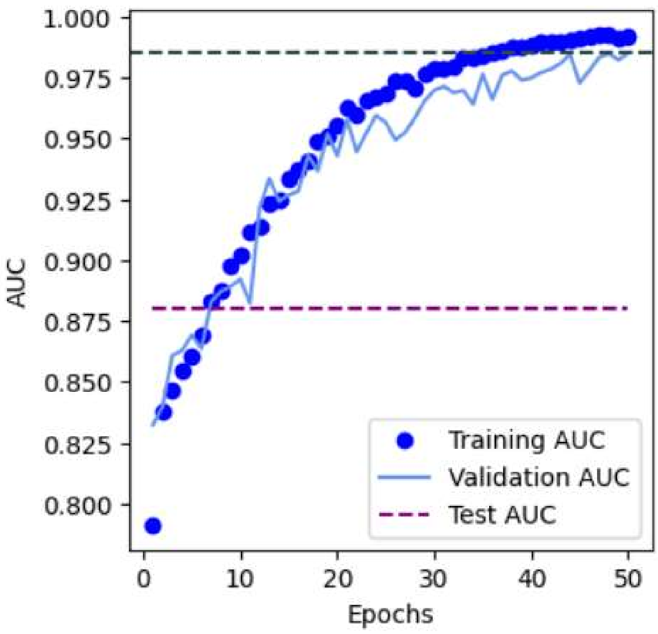

Figure 5b: Validation AUC by Epochs

7. Confusion Matrix:

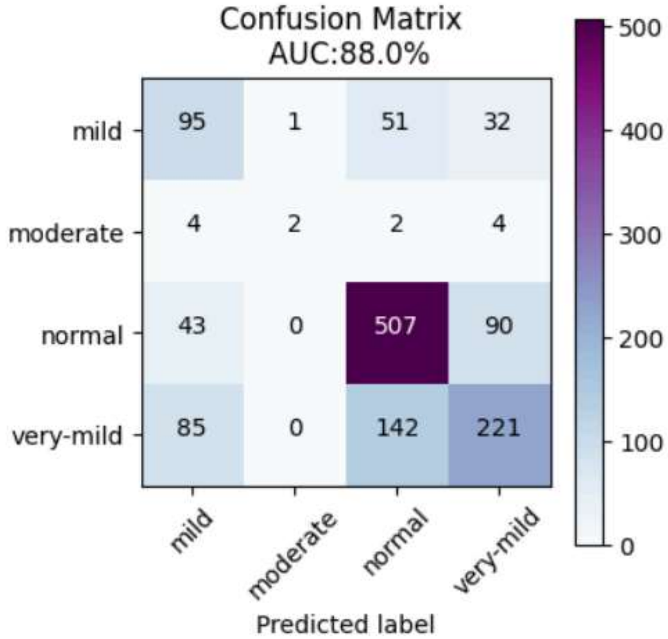

Figure 7: Confusion Matrix

The confusion matrix as represented in Fig 7 indicated that the model does best at identifying normal and very-mild MRIs and poorest identifying moderate cases. This makes sense given the small number of moderate examples in the dataset. Adding model capacity, searching for optimal hyperparameters and adding data augmentation resulted in better performance on the test dataset.

C] Testing Cognitive Power of a Brain :

MMSE - Mini-Mental State Examination: We integrated the Mini-Mental State Examination (MMSE) as a standardized tool for assessing cognitive function in Alzheimer's disease (AD) patients. The MMSE consists of a series of questions and tasks that evaluate various aspects of cognitive function, including orientation, memory, attention, and language skills. Patients are scored based on their performance, with scores ranging from 0 to 30. Lower scores indicate greater cognitive impairment.

The MMSE test is an essential component of our project as it provides healthcare providers with valuable insights into the progression of AD. By regularly administering the MMSE test, healthcare providers can track changes in cognitive function over time and tailor treatment plans to meet the individual needs of patients. This proactive approach allows for timely interventions that can help slow the progression of the disease and improve patient outcomes.

Cognitive Games: These games are designed to stimulate various cognitive functions, including memory, attention, and problem-solving skills. By engaging in these games regularly, AD patients can maintain and improve their cognitive abilities, which can help enhance their overall quality of life.

VII. Conclusion

Our project, titled "Cognitive Care," presents a significant advancement in the early detection and personalized management of Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI). With an achieved accuracy of 78%, our software marks a promising step towards improving AD and MCI detection. However, the full realization of our project aims to deliver a groundbreaking software solution that not only facilitates early detection but also offers personalized recovery assessment and progress tracking. By leveraging advanced data analysis techniques and machine learning-driven predictions, our software has the potential to revolutionize the management of cognitive disorders, ultimately enhancing patient outcomes and contributing to our understanding of cognitive recovery.

Through the integration of Agile development principles and a focus on surpassing existing systems, our project, "Cognitive Care," distinguishes itself by empowering patients on their journey towards cognitive improvement. Our collaborative efforts involving medical expertise, software development, and iterative refinement have resulted in a solution that addresses the complexities of AD and MCI. Moving forward, approval from verified and top doctors in the field will provide further validation and impetus to our application. Additionally, we recognize the importance of a simpler and more interactive user interface to ensure greater user participation and superior user experience. These features, along with our commitment to societal impact, set our application apart and highlight its significance in advancing the field of cognitive disorder management. Future research could focus on refining the software further and exploring additional avenues for enhancing patient care and outcomes in cognitive disorders.

VIII. Future Scope

This project achieves all the functionalities it aimed to achieve in the first place. One of the paths we can explore is using a multi model approach to detect Alzheimer's and provide a much more comprehensive result by incorporating all the results from various models used. We can also use a transfer learning model to predict and classify Alzeimers for the patients. So these are some directions our project could be moved in.

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