Cognitive Care

Submitted in partial fulfillment of the requirements of the degree

BACHELOR OF ENGINEERING IN **COMPUTER ENGINEERING**

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CERTIFICATE

This is to certify that the Mini Project entitled **“Cognitive Care”** is a bonafide work of **Rishi Kokil (D12C-38) Amit Murkalmath (D12C-47) Ilham Syed (D12C-61) Pavan Thakur (D12C-67)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **“Bachelor of Engineering”** in **“Computer Engineering” .**

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Mini Project Approval

This Mini Project entitled "**Cognitive Care**" by **Rishi Kokil (D12C-38) Amit Murkalmath (D12C-47) Ilham Syed (D12C-61) Pavan Thakur (D12C-67)** is approved for the degree of **Bachelor of Engineering** in **Computer Engineering.**

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Contents

Abstract

This project presents a pragmatic solution for addressing the pressing challenges posed by Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) through the combination of Health Expertise and modern technology. Leveraging Machine Learning (ML) methodologies, we aim to develop a robust software platform that advances early detection, offers personalized treatment recommendations, and enhances patient recovery. By bridging clinical expertise with data-driven analyses, our software seeks to unravel patterns within intricate neurological data, providing a comprehensive framework for informed decision-making in AD and MCI management. Through a mixture of Medical Sciences and ML innovation, By bringing about a future of proactive care and better patient outcomes, we anticipate a transformational influence on the diagnostic and treatment landscape of cognitive diseases.

In the subsequent sections of this synopsis, we explore the methodology, data sources and anticipated outcomes of our Machine Learning-based software for AD and MCI detection, treatment suggestions, and patient recovery. Through joint efforts at the interface of medical science and artificial intelligence, we aim to reshape the trajectory of cognitive disorders and foster a brighter future for patients and their families.

Acknowledgement

We extend our heartfelt gratitude to the individuals and organizations who have played an important role in the realization of this project, which aims to make a profound impact on Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) management through the fusion of medical expertise and modern technology.

First and foremost, we would like to express our deepest appreciation to our project mentor, Dr. Gresha Bhatia, Deputy Head of the Department (CMPN), for her unwavering support and invaluable guidance throughout the course of this project. Her knowledge and commitment for our project have been instrumental in shaping our vision. We are sincerely grateful for her mentorship. We also extend our appreciation to our institution, Vivekanand Education Society's Institute of Technology, for providing us with the infrastructure and a conducive environment for conducting our research and development.

Furthermore, we acknowledge the contribution of the Kaggle community for making their comprehensive dataset available, which served as the foundation of our research. The wealth of data and collaborative spirit within the Kaggle platform significantly facilitated the development of our Machine Learning-based software. We extend our appreciation to all the members of our project team who put in tireless hours and collective effort into this endeavor. Each individual's dedication, from the conceptualization stage to the implementation, has been critical to our project's success.

Overall, it is through the collective efforts and support of these individuals and institutions that we have been able to embark on this journey in the field of cognitive disorder management. We hope that our project will make a meaningful impact on the lives of individuals and families affected by AD and MCI, and we look forward to contributing to a brighter future in the field of healthcare.

Sincerely,
TE Mini Project
Group - 05 CMPN

List of Abbreviations

- AD: Alzheimer’s Disease
- MCI: Mild Cognitive Impairment
- ML: Machine Learning
- MRI: Magnetic Resonance Imaging
- CNN: Convolutional Neural Networks
- ADNI: Alzheimer's Disease Neuroimaging Initiative
- NC: Normal Condition
- pMCI: progressive MCI
- sMCI: stable MCI
- DTI: Diffusion Tensor Imaging
- MD: Mean Diffusivity
- MMSC: Mini Mental State Examination
- LSTM: Long Short Term Memory
- MTL: Medial Temporal Lobe
- PET: Positron Emission Tomography
- CT: Computerized Tomography
- MTA: Medial Temporal Atrophy
- CSF: Cerebral Spinal Fluid
- UI: User Interface
- ROC: Receiver Operating Characteristic Curve
- GPU: Graphics Processing Unit
- SSD: Solid State Drive
- RNN: Recurrent Neural Networks

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Introduction

1.1 Introduction

The advancements in medical imaging and machine learning have opened new avenues for the early detection and management of complex neurological conditions such as Alzheimer's disease and Mild Cognitive Impairment (MCI). Magnetic Resonance Imaging (MRI) scans, with their ability to reveal intricate structural details of the brain, have become a valuable resource for comprehending cognitive disorders. This project aims to harness the potential of machine learning to detect Alzheimer's disease and MCI through analysis of MRI scans. Additionally, recognizing the need for comprehensive care, the project also undertakes the development of an innovative recovery algorithm. This synergy of advanced data analysis and recovery algorithm development, the project aspires to significantly impact the early diagnosis and management of cognitive disorders.

1.2 Motivation

Alzheimer’s Disease is a very common disease and it's very rampant and many of the times overlooked by society. Alzheimer’s disease (AD) and other forms of dementia are a growing public health problem among the elderly in developing countries, whose aging population is increasing rapidly. Studies say estimated dementia prevalence for adults ages 60+ in India is 7.4%, with significant age and education gradients, sex and urban/rural differences, and cross-state variation. An estimated 8.8 million Indians older than 60 years have dementia. The burden of dementia cases is unevenly distributed across states and subpopulations and may therefore require different levels of local planning and support. These were some of the facts that forced us to realize that it's a grave issue which needs to be addressed and an effective solution needs to be built for the same. Also one of our group members’ relatives suffered from the same and the said relative recently passed away. This kind of gave our project a different push and meaning. So we were more than determined to make sure our project reached the masses and served the purpose it was intended to do. Thus, these were some of the points that motivated us to choose this project.

1.3 Problem Statement and Objectives

Alzheimer's disease and Mild Cognitive Impairment (MCI) stand as prominent challenges in modern healthcare due to their progressively debilitating impact on cognitive function and quality of life. With the help of technology and advancements in medical imaging the project aims to develop an innovative and user-friendly software solution that can accurately identify individuals with Alzheimer's disease or Mild Cognitive Impairment (MCI) and also provide personalized recovery measures and progress tracking for individuals diagnosed with these conditions.

2. Literature Survey

Performing a literature survey in a research paper is a fundamental step that serves multiple crucial purposes. Firstly, it provides context and background information, allowing readers to comprehend the problem's significance and what has previously been investigated in the field. By thoroughly reviewing existing literature, researchers can pinpoint gaps, inconsistencies, or areas where additional research is required, helping to define their research question and scope. This process also enables researchers to build upon the work of others, advancing the field and demonstrating that their research is a meaningful contribution to an ongoing scholarly conversation. Moreover, it aids in the avoidance of duplicating studies that have already been conducted, emphasizing originality.

2.1 Survey of Existing System

1. **M. Talo, O. Yildirim, U. B. Baloglu, G. Aydin, and U. R. Acharya, “Convolutional neural networks for multi-class brain disease detection using MRI images,” *Computerized Medical Imaging and Graphics*, p. 101673, Oct. 2019, doi: https://doi.org/10.1016/j.compmedimag.2019.101673.**

Abstract :- The importance of early detection of brain disorders and the challenges associated with manual diagnosis using MRI images. To address these challenges, the study employs deep learning models, including AlexNet, Vgg-16, ResNet-18, ResNet-34, and ResNet-50, to automatically classify MR images into various disease classes. The research compares their performance and identifies ResNet-50 as the most accurate model, achieving a classification accuracy of 95.23% ± 0.6. The study highlights the potential for this model to be used for testing with a large dataset of MRI images, aiding clinicians in validating their findings after manual examination.

Findings :- Application of convolutional neural networks (CNNs) for the multi-class classification of brain diseases using MRI images. Aim to develop an automated system that can accurately classify brain MRI images into different disease categories, including normal, cerebrovascular, neoplastic, degenerative, and inflammatory diseases. Comparing the performance of different pre-trained CNN models, such as AlexNet, Vgg-16, ResNet-18, ResNet-34, and ResNet-50.

2. **S. El-Sappagh et al., “Alzheimer’s disease progression detection model based on an early fusion of cost-effective multimodal data,” Future Generation Computer Systems, vol. 115, pp. 680–699, Feb. 2021, doi: https://doi.org/10.1016/j.future.2020.10.005.**

Abstract :- This study focuses on predicting Alzheimer's disease (AD) progression over 2.5 years. It compares five machine learning algorithms using data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. What makes this research unique is the inclusion of time-series features such as patient comorbidities, cognitive scores, medication history, and demographics, along with semantic preparation of medication and comorbidity text data. The results show that early fusion of these features significantly improves predictive power, with the random forest model performing the best. This study is the first of its kind to explore the role of multimodal time-series data in AD prediction.

Findings :- 4-class classification (CN, sMCI, pMCI, AD).Testing model performance with different datasets. Assessing the importance of features and drug groups.Developing cost-effective models for AD prediction using readily available patient data.

3. **A. De and A. S. Chowdhury, "DTI based Alzheimer's disease classification with rank modulated fusion of CNNs and random forest,"** ***Expert Systems with Applications*****, vol. 169, p. 114338, May 2021, doi: https://doi.org/10.1016/j.eswa.2020.114338.**

Abstract :- The paper introduces a novel approach for automating the classification of Alzheimer's disease (AD) and related conditions. It uses 3D Diffusion Tensor Imaging (DTI) data, including FA, MD, and EPI intensities. The authors employ Convolutional Neural Networks (CNNs) and a Random Forest Classifier (RFC) for separate training and evaluation. By combining the results using a fusion strategy, they achieve a high classification accuracy of 92.6%. This approach is validated through extensive experiments on the ADNI database, showing its effectiveness in diagnosing AD and related conditions.

Findings :- Classification of Alzheimer's disease using Diffusion Tensor Imaging (DTI) data. Proposed method that combines Convolutional Neural Networks (CNNs) and Random Forest Classifier (RFC) to classify different stages of Alzheimer's disease

4. **M. Rohanian, J. Hough, and M. Purver, "Multi-Modal Fusion with Gating Using Audio, Lexical and Disfluency Features for Alzheimer's Dementia Recognition from Spontaneous Speech," Interspeech 2020, Oct. 2020, doi: https://doi.org/10.21437/interspeech.2020-2721.**

Abstract :- This paper is a submission to the ADReSS challenge, which aims to predict the severity of Alzheimer's Disease using speech data. The authors focus on acoustic and natural language features in spontaneous speech and their connection to Alzheimer's diagnosis and the mini-mental state examination (MMSE) score prediction. They propose a model that uses separate Long Short-Term Memory (LSTM) networks for text and audio data and combines their outputs with a gating mechanism for the final prediction.

Findings :- Study of markers associated with Alzheimer's disease (AD) severity.The document aims to explore lexical markers, disfluency markers (specifically self-repair), and structural markers (with a focus on grammatical fluency) in relation
to AD severity.

5. **X. Zheng, J. Cawood, C. M. Hayre, and S. Wang, "Computer assisted diagnosis of Alzheimer's disease using statistical likelihood-ratio test,"** ***PLOS ONE*****, vol. 18, no. 2, pp. e0279574–e0279574, Feb. 2023, doi: https://doi.org/10.1371/journal.pone.0279574.**

Abstract :- This study employs a statistical likelihood-ratio approach based on signal detection theory. The tool calculates the likelihood ratio using the medial temporal lobe (MTL) volumes obtained from Alzheimer's disease (AD) patients and normal controls (NC). These volume measurements are derived from T1-weighted MRI images using FreeSurfer software. The MRI images come from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database, and a separate dataset called Minimal Interval Resonance Imaging in Alzheimer's Disease (MIRIAD) is used for testing. The results show a sensitivity of 89.1% and a specificity of 87.0% for the MIRIAD dataset. These results surpass the performance of the best radiologists, who achieved 85% sensitivity and specificity without using additional patient information.

Findings : - The main focus area of the given paper is the development and validation of a statistical likelihood-ratio procedure for the detection of Alzheimer's disease using MRI T1 weighted images. Specifically, the study focuses on the medial temporal lobe (MTL) volumes of patients with AD and normal controls (NC).

6. **A. Shukla, R. Tiwari, and S. Tiwari, "Review on Alzheimer Disease Detection Methods: Automatic Pipelines and Machine Learning Techniques,"** ***Sci*****, vol. 5, no. 1, p. 13, Mar. 2023, doi: https://doi.org/10.3390/sci5010013.**

Abstract :- Alzheimer's Disease (AD) is becoming increasingly prevalent across the globe, and various diagnostic and detection methods have been developed in recent years. Several techniques are available, including Automatic Pipeline Methods and Machine Learning Methods that utilize Biomarker Methods, Fusion, and Registration for multimodality, to pre-process medical scans. The use of automated pipelines and machine learning systems has proven beneficial in accurately identifying AD and its stages, with a success rate of over 95% for single and binary class classifications. However, there are still challenges in multi-class classification, such as distinguishing between AD and MCI, as well as sub-stages of MCI. The research also emphasizes the significance of using multi-modality approaches for effective validation in detecting AD and its stages.

Findings :- The focus area of the paper is on the detection of Alzheimer's disease (AD) using automated pipelines and fusion-based methods. The paper discusses the challenges in multi-class classification, such as distinguishing between AD and mild cognitive impairment (MCI) and sub-stages of MCI. It emphasizes the significance of using multi-modality approaches, including MRI, PET, and CT modalities, for effective validation in detecting AD and its stages. The paper also explores the importance of pre-processing techniques for feature extraction and the use of machine learning and deep learning algorithms in AD detection.

2.2 Limitation Existing system or Research gap

- **Limited labeled data** :- There is a deficiency of publicly available large datasets for research, limiting the availability of labeled datasets for Alzheimer's disease detection and so it affects model accuracy and study comprehensiveness.
- **Class Imbalance**: Imbalance in the number of samples between different classes (AD, MCI, normal) can affect the performance of machine learning algorithms.
- **Lack of Detailed Model Information:** Inadequate information about model architecture, training procedures, and hyperparameter settings impedes transparency and replicability.
- **Limited Use of Fusion Approaches**: The limited utilization of fusion techniques for combining information from various sources hampers performance.
- **Single Biomarker Focus**: Concentrating solely on medial temporal lobe atrophy (MTA) overlooks the potential benefits of integrating other biomarkers, such as cerebrospinal fluid analysis (CSF) and Positron Emission Tomography (PET) imaging, in Alzheimer's diagnosis.
- **Data Quality Concerns** :Poor-quality images during pre-processing can negatively impact Alzheimer's disease detection accuracy.
- **Omission of Influential Factors**: Neglecting factors like gender, brain size, and age corrections in brain volume calculations could impact diagnostic accuracy.
- **Clarity of Frameworks:** Some proposed frameworks lack clear explanations, making it difficult for others to replicate results and advance the field.

2.3 Mini Project Contribution

Our mini project titled “Cognitive Care” to detect Alzheimers’ Disease overcomes a lot of problems faced by the current system. Our project combines Agile development principles and also aims to give much better results than the existing systems. Our system aims to not only enable intervention and provide detection like other systems but also empower patients on their journey towards cognitive improvement. Through the collaborative efforts of medical expertise, software development, and iterative refinement, we aim to create a meaningful and impactful solution that addresses the complexities of Alzheimer's disease and MCI. And approval from verified and top doctors in the field would give an impetus to our application too. A much simpler and interactive UI would ensure more user participation and superior user experience. Thus, these are some of the main features that sets us apart from the rest of the other systems and how our application contributes to society.

3. Proposed System

3.1 Introduction

Our proposed solution strives to contribute significantly to the field of cognitive healthcare by combining Agile development principles. This approach not only enables early intervention and accurate detection but also empowers individuals on their journey towards cognitive improvement. Through the collaborative efforts of medical expertise, software development, and iterative refinement, we aim to create a meaningful and impactful solution that addresses the complexities of Alzheimer's disease and MCI. Also, recognizing the significance of user-friendliness, we will design an intuitive interface for both healthcare professionals and patients. This interface will enable easy input of MRI data, visualization of diagnostic results, and clear presentation of personalized recovery recommendations. Iterative development under the Agile model allows us to adjust the interface based on user feedback, ensuring it remains intuitive and efficient.

3.2 Methodology / Block Diagram

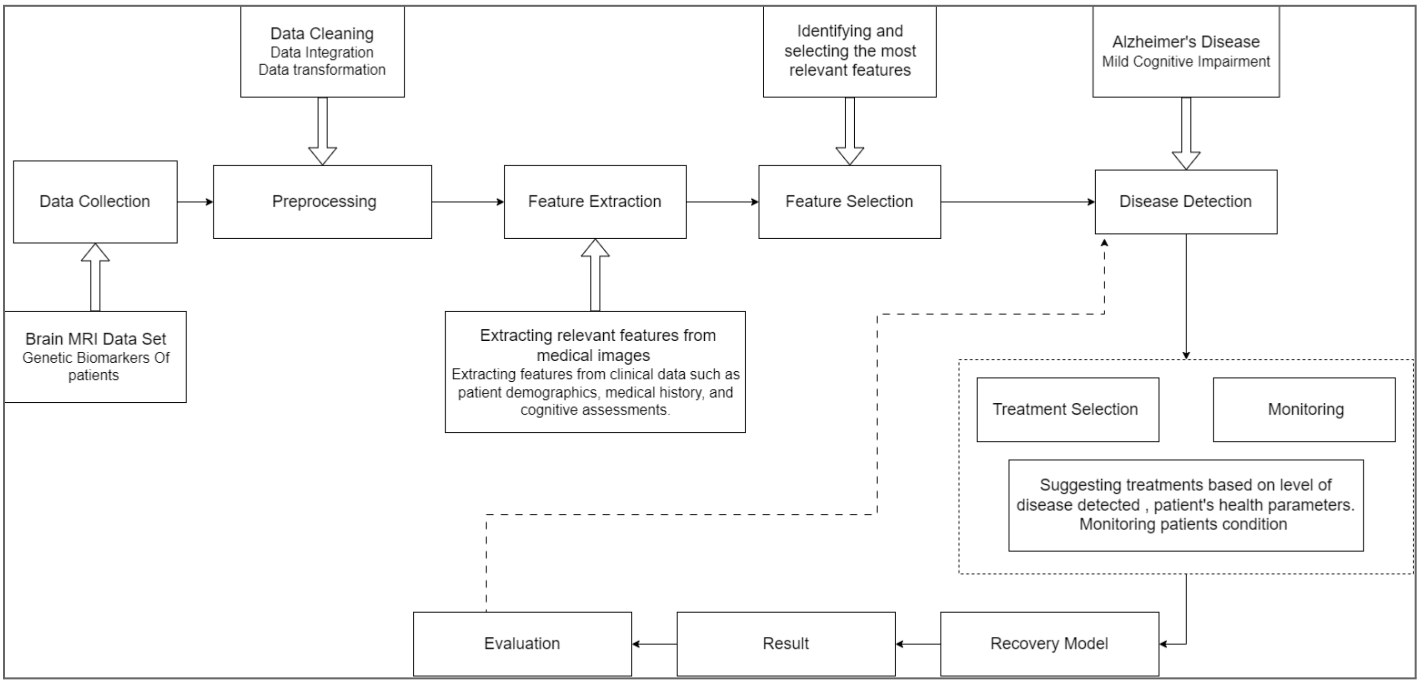

Fig 1 : Block Diagram of Our System

3.3 Algorithm and process design

Algorithm:
Convolutional Neural Network (CNN) - A CNN algorithm suitable for image analysis, tailored to the specific requirements of AD and MCI detection. Include multiple convolutional layers, pooling layers, and fully connected layers. Implement techniques like dropout and batch normalization to prevent overfitting.

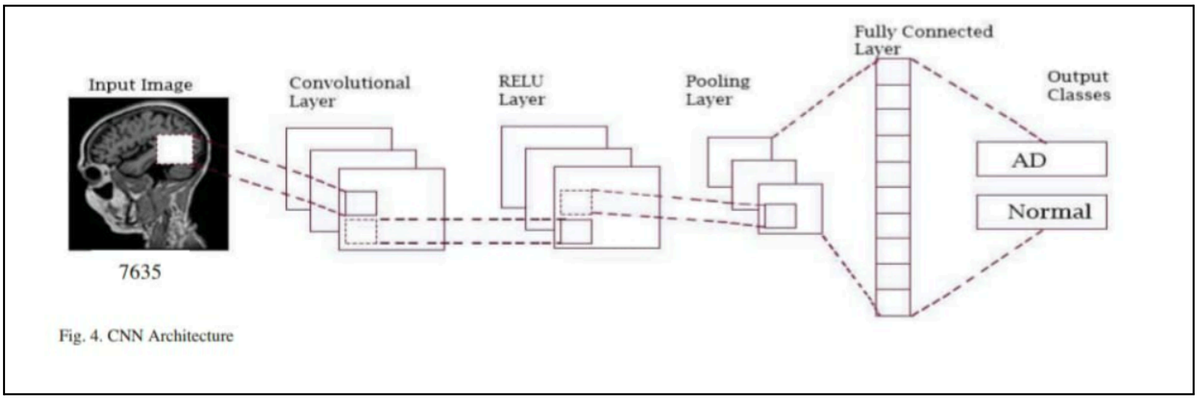

Fig 5: A diagram explaining CNN Model

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 148, 148, 32)      896

 max_pooling2d (MaxPooling2  (None, 74, 74, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 72, 72, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 36, 36, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 34, 34, 128)       73856

 max_pooling2d_2 (MaxPoolin  (None, 17, 17, 128)       0
 g2D)

 flatten (Flatten)           (None, 36992)             0

 dense (Dense)               (None, 128)               4735104

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 4828481 (18.42 MB)
Trainable params: 4828481 (18.42 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig 6: CNN Model Summary

Process Design:

1. **Data Collection and Preprocessing**: Obtain Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) datasets from Kaggle. Preprocess the data to remove noise, handle missing values, and ensure data consistency. Data augmentation techniques are applied to increase the dataset size and diversity.

2. **Feature Extraction**: Extract relevant features from the neurological data, such as brain scans (e.g., MRI images) and patient records. Feature selection techniques may be used to identify the most informative variables.

3. **Model Training for AD's detection**: Split the dataset into training, validation, and test sets. Train the CNN model using the training set with a loss function categorical cross-entropy and optimization algorithm. We monitored the model's performance on the validation set to prevent overfitting.

4. **Model Evaluation**: Evaluated the trained CNN model's performance on the test set using metrics such as accuracy, precision, recall, F1 score, and area under the ROC curve (AUC).

5. **Personalized Treatment Recommendation** : We are planning to implement an algorithm to provide personalized treatment recommendations based on the patient's diagnosis and historical data. Use machine learning techniques to analyze treatment response data and tailor recommendations accordingly.

6. **User Interface Development**: We have created a user-friendly interface for clinicians or users to input patient data and view diagnostic results and treatment recommendations.

This algorithm and process design outlines the steps involved in developing a CNN-based software platform for AD and MCI detection, personalized treatment recommendations.

3.4 Methodology Applied

Agile Development : Our choice of the Agile software development model allows us to be nimble in our approach. We have broken the project into smaller, manageable phases called sprints. In each sprint, we'll develop specific features, such as refining the MRI analysis algorithm or enhancing the recovery plan generator and adding new functionality to our website. This iterative process enables us to continuously gather feedback from healthcare experts and potential end-users, refining the software's functionality to match evolving requirements.

3.5 Hardware , Software and tools Requirements

Hardware Requirements:

- **CPU**: A modern multi-core processor (e.g Intel Core i5 or higher, AMD Ryzen 5 or higher) is sufficient for basic machine learning tasks and small datasets.
- **RAM**: At least 8 GB of RAM is recommended for handling medium-sized datasets and training relatively small models. However, having 16 GB or more will be beneficial for larger datasets and more complex models.
- **GPU** (**Optional**): A dedicated graphics processing unit (GPU) is not strictly required, but having one can significantly speed up training times, especially for deep learning models.

- **Storage**: A solid-state drive (SSD) is recommended for faster data read/write speeds, which can be beneficial when working with large datasets. A capacity of 256 GB or more is preferable to accommodate datasets and model checkpoints.
- **Operating System**: You can work on machine learning tasks using Windows, macOS, or Linux.

Software Requirements:

- **Python and Libraries**: Python version 3.6 or higher and essential libraries for machine learning, such as NumPy, pandas, scikit-learn, TensorFlow, keras and PyTorch.

  Machine Learning Frameworks:
  - **TensorFlow (version 2.13.0)**: TensorFlow is designed to efficiently handle large-scale computations, making it well-suited for training complex deep learning models on powerful GPUs or distributed computing clusters. PyTorch uses a dynamic computation graph, which allows for more intuitive debugging and flexible model architectures. This makes it easier to work with irregular and varying input data shapes.
  - **Scikit-learn (version 1.3.0)** : Scikit-learn offers a rich set of functionalities for data preprocessing, including handling missing values, feature scaling, and encoding categorical variables. This step is essential to prepare the data for modeling.
  - **Keras (version 3.7.2)** : Keras supports building a wide range of neural network architectures, including feedforward networks, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers. It allows easy customization of layers, activation functions, and optimization algorithms.
- **Web Development Technologies :**
  - **Programming Languages used :-** HTML(version 5), CSS (level 3) , Javascript (ECMAScript 6)
  - **Frameworks used** :- React JS(version 18.2.0) , Tailwind CSS (version 3.0) , NodeJS (version 7.10.1 or higher) and Express JS(4.18.2).
  - **Database** :- Mongodb(version 7.0) and Mongoose(version 7.6.3).

3.6 Experiment and Results for Validation and Verification explanation

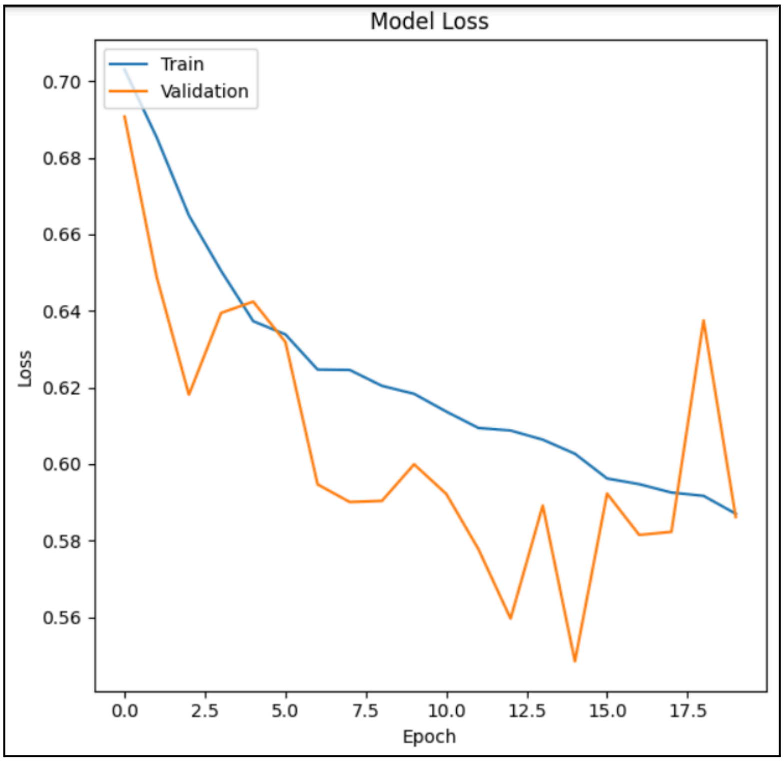

Fig 2 : Epoch vs Loss line chart

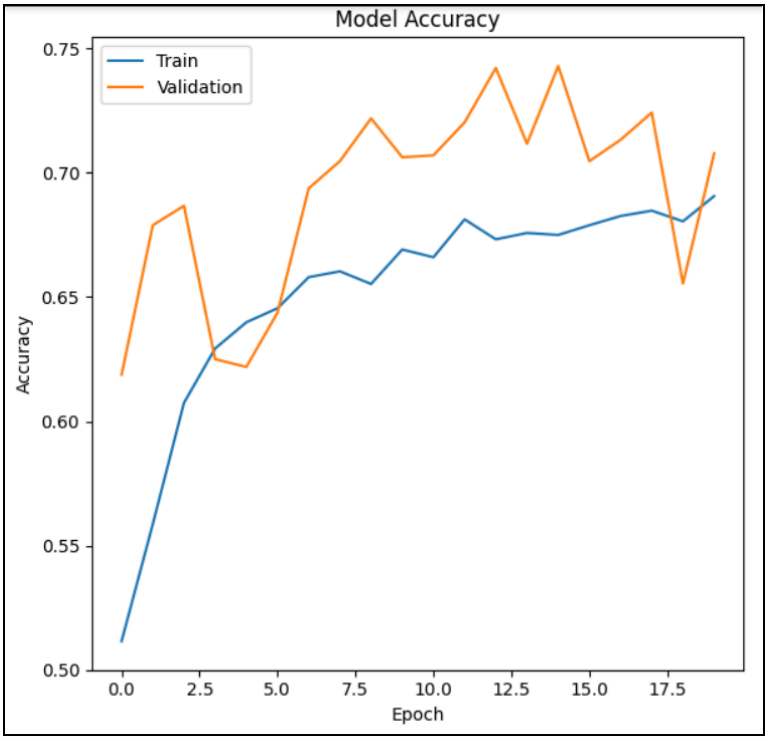

Fig 3 : Epoch vs Accuracy line chart

```
Epoch 14/15
160/160 [==============================] - 49s 307ms/step - loss: 0.5917 - accuracy: 0.6805 - val_loss: 0.6375 - val_accuracy: 0.6555
Epoch 15/15
160/160 [==============================] - 51s 322ms/step - loss: 0.5870 - accuracy: 0.6906 - val_loss: 0.5861 - val_accuracy: 0.7078
40/40 [==============================] - 10s 256ms/step - loss: 0.5909 - accuracy: 0.7078
Test accuracy after additional epochs: 0.707812488079071
```

Fig 4 : Model training results

Testing the Model:

```
import numpy as np
from keras.preprocessing.image import load_img, img_to_array
import matplotlib.pyplot as plt

def predict_dementia(image_path, model, image_size=(150, 150)):

  img = load_img(image_path, target_size=image_size)
  img_array = img_to_array(img)
  img_array = np.expand_dims(img_array, axis=0)
  img_array /= 255.0
  plt.imshow(img)
  plt.axis('off')
  plt.show()
  # Using the trained model for prediction
  predictions = model.predict(img_array)
  # Interpreting the prediction
  if predictions[0] > 0.5:
    result = "Non-Dementia"
  else:
    result = "Dementia"
  return result
```

```
prediction_result = predict_dementia('/content/moderate_2.jpg', model)
print(f"The MRI image indicates: {prediction_result}")
```

```
1/1 [==============================] - 0s 94ms/step
The MRI image indicates: Dementia
```

Fig 7. Model Testing

3.7 Result Analysis and Discussion

Formulas:

Precision $= \dfrac{True\ Positive}{True\ Positive + False\ Positive} \rightarrow \dfrac{TP}{TP + FP}$

Accuracy $= \dfrac{True\ positives + True\ Negatives}{True\ positives + True\ negatives + False\ positives + False\ negatives} \rightarrow \dfrac{TP + TN}{TP + TN + FP + FN}$

Recall $= \dfrac{True\ Positive}{True\ Positive + False\ Negative} \rightarrow \dfrac{TP}{TP + FN}$

True Positive (TP): The number of correctly identified positive instances by the software.

False Positive (FP): The number of instances that the software incorrectly identifies as positive when they are actually negative.

True negative(TN) :- The Number of outcomes where the model correctly predicts the negative class.

False Negative (FN) :- The Number of outcomes where the model incorrectly predicts the positive class.

```
Confusion Matrix:
[[441 199]
 [441 199]]
Precision: 0.5
Recall: 0.3109375
```

Fig 8: Confusion Matrix value

1. Accuracy and Evaluation Metrics:
   - **Accuracy**: The achieved accuracy of 70.78% demonstrates the model's ability to classify AD and MCI cases correctly.
   - **Precision and Recall**:

2. Confusion Matrix: The confusion matrix is a valuable tool for understanding the distribution of true positive, true negative, false positive, and false negative predictions. It provides insights into the model's strengths and weaknesses.
3. Feature Importance: The importance of different features or layers in the CNN model to identify which aspects of the data had the most significant influence on the classification.
4. Real-World Applicability: The achieved accuracy of 70.78% for early detection of Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI), aligning with the project's goals, offers the potential to enhance the real-world management of cognitive disorders through more timely interventions.

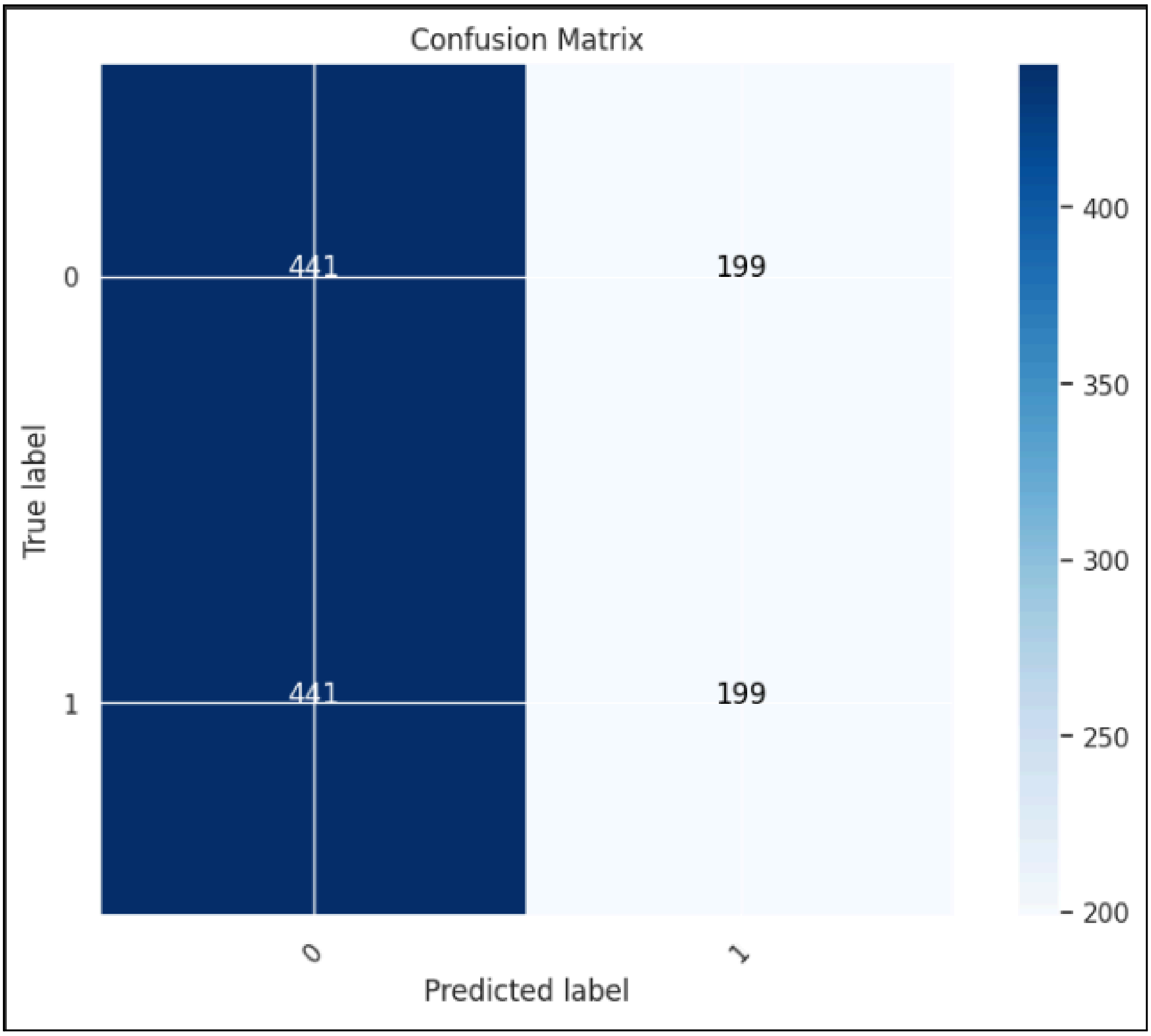

Fig 9. Confusion Matrix

3.8 Conclusion and Future Work

The achieved accuracy of 78% is a promising step forward in the journey to improve the early detection of AD and MCI. However, the successful completion of this project will result in a groundbreaking software solution that not only aids in the early detection of Alzheimer's disease and MCI but also offers a novel approach to personalized recovery assessment and progress tracking. By combining advanced data analysis techniques with machine learning-driven predictions, this software has the potential to revolutionize the way cognitive disorders are managed, enhancing patient outcomes and contributing to our understanding of cognitive recovery.

Our next step of action includes :

- Developing Proper User Interface and more sophisticated backend development.
- Training our AI model to deliver more accurate results.
- Contacting more organizations for collaboration with our project.
- Classifying patients into the categories of mild, moderate and extreme dementia more effectively and efficiently.
- Researching more outcome and result oriented treatment plans and doctor recommended remedies to be given to a patient after a successful diagnosis.

4. References

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