ALZHEIMER SYNDROME RECOGNITION USING DENSENET FOR MULTIMODAL ANALYSIS

PROJECT -II REPORT

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

ABSTRACT

Alzheimer's syndrome is a progressive disorder affecting memory and cognition, requiring early diagnosis for effective treatment. Deep learning, especially multimodal analysis, integrates MRI scans, PET images, and clinical data for improved assessment. A pre-trained model densenet, enhances feature propagation and classification accuracy by mitigating vanishing gradients. It classifies brain scans into four stages, capturing different levels of cognitive decline and structural changes. Fine-tuning DenseNet on diverse data improves prediction accuracy and estimates disease progression. This aids clinicians in personalized treatment planning and enhances communication among healthcare providers and families. The Multimodal detects intricate brain atrophy patterns, functional impairments, and white matter integrity changes. Hierarchical learning in DenseNet enables the identification of both basic textures and complex structural variations. Predictive capabilities assist in early intervention, optimizing care strategies for patients. Integrating VGG-16 with multimodal analysis revolutionizes Alzheimer's detection, improving diagnostic precision and patient outcomes. This capability fosters better communication between healthcare providers, patients, and families about treatment options. Overall, integrating deep learning with MRI analysis signifies a major advancement in the early detection and management of Alzheimer's syndrome. This advanced approach enhances early interventions and optimizes treatment plans, leading to better patient care. By leveraging multimodal analysis with DenseNet, Alzheimer's diagnosis becomes more precise and effective.

Keywords: DenseNet, Neuro Imaging, Convolutional Neural Network, MRI Scans.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF ABBREVATIONS

SYMBOLS	ABBREVIATIONS
MRI	Magnetic Resonance Image
CNN	Convolutional Neural Network
DenseNet	Densely Connected Network
DL	Deep Learning
AD	Alzheimer’s Disease
MCI	Mild Cognitive Impairment
VGG-16	Visual Geometry Group -16

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

Alzheimer's syndrome is a progressive neurodegenerative disorder that severely impacts memory, cognitive function, and daily life. Early and accurate diagnosis is crucial for effective treatment and management, as timely interventions can significantly enhance patient outcomes. With the rising prevalence of Alzheimer's, particularly among the elderly, the demand for reliable diagnostic tools has become increasingly urgent. This project focuses on developing an automated system for recognizing Alzheimer's disease using Deep learning techniques. By leveraging advanced algorithms and medical data, we aim to create an efficient and accurate model capable of identifying early signs of Alzheimer's from brain scans or other relevant biomarkers.

Using multimodal analysis, it integrates MRI scans, PET images, and clinical data for a comprehensive assessment. DenseNet's architecture, with densely connected layers, enhances feature propagation and gradient flow, improving classification accuracy. By analyzing patterns of brain atrophy, functional impairments, and structural variations, it identifies key Alzheimer's-related biomarkers. Fine-tuning DenseNet on a diverse dataset improves predictive accuracy and generalization, aiding in early detection and disease progression analysis. This deep learning model extracts hierarchical features, from simple textures to complex structural changes, enhancing diagnostic precision. Leveraging multimodal data with DenseNet significantly improves Alzheimer's detection, enabling personalized treatment planning and better patient outcomes.

DenseNet based multimodal analysis integrates MRI, PET, and clinical data to enhance Alzheimer's detection accuracy. Its deep feature extraction enables early diagnosis and personalized treatment strategies for improved patient care.

In Alzheimer’s disease recognition, we employed multimodal analysis by integrating key domains such as MRI scans, PET images, and clinical data with advanced deep learning architectures, specifically DenseNet. MRI and PET images provide complementary insights into both structural and functional brain changes, enabling a more comprehensive assessment of Alzheimer’s progression. These imaging modalities help detect critical biomarkers like cortical thinning, hippocampal atrophy, and metabolic abnormalities, which are strong indicators of cognitive decline.

Implemented DenseNet due to its densely connected layers, which enhance feature propagation and mitigate vanishing gradients, ensuring efficient learning from complex medical data. This architecture excels at capturing intricate patterns and subtle changes in brain structure, making it highly suitable for early-stage Alzheimer’s detection. VGG-16 is highly effective at extracting hierarchical features, from basic textures to complex structural representations, which helps in distinguishing between different stages of Alzheimer’s.

Training the model on a diverse, labeled dataset of multimodal inputs improves classification accuracy and enhances the system’s ability to predict disease progression. The integration of MRI, PET, and clinical data within a deep learning framework results in a robust and reliable method for detecting Alzheimer’s and estimating its severity. This approach represents a significant advancement in medical imaging and early diagnosis, providing clinicians with a powerful tool for personalized treatment planning and improved patient outcomes. By leveraging multimodal data with DenseNet, we have developed an advanced system for classifying Alzheimer’s progression with greater precision and reliability. The use of these architectures allows for accurate detection of subtle brain changes. By combining these domains, to develope a robust and accurate system for classifying Alzheimer's progression based on MRI scans.

CHAPTER 2

LITERATURE SURVEY

2.1 Uttam Khatri, Jun-Hyung, Goo-Rak Kwon.,"Alzheimer's Disease and Mild Cognitive Impairment Detection MRI With Efficient Receptive Field and an Enhanced Multi-Axis Attention Fusion.,"2024.

The methodology involves using MRI scans for detecting Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI). An Efficient Receptive Field mechanism is applied to capture critical brain regions with enhanced sensitivity. A Multi-Axis Attention Fusion (MAAF) approach is then employed to integrate information across multiple brain regions and axes, improving the model's ability to focus on key features. Deep learning techniques, such as Convolutional Neural Networks (CNNs), are used for feature extraction and classification. The model is trained on a dataset of MRI images, where it learns to distinguish between normal, MCI, and AD cases by focusing on structural changes. Fine-tuning is done to improve accuracy, and performance metrics are assessed for validation.

The deep learning model is trained on a diverse dataset, including images from healthy individuals and those diagnosed with MCI and AD. This approach aims to provide robust and accurate classifications, improving early diagnosis and intervention strategies. By combining these advanced techniques, the study enhance diagnostic precision and facilitate timely treatments for patients. Ultimately, this research contributes to the ongoing efforts to leverage artificial intelligence in the field of neuroimaging and cognitive health.

Key Points

- Improved model performance due to the integration of efficient receptive fields for better focus on important features.
- Early detection enables timely interventions, which can slow disease progression and improve patient outcomes.
- Increased diagnostic precision, facilitating timely interventions for patients with MRI and AD.

2.2 Battula Srinivasa Rao, Mudiyala Aprana.," A Review on Alzheimer's Disease Through Analysis of MRI Images Using Deep Learning Techniques.," 2024.

A Review on Alzheimer's Disease Through Analysis of MRI Images Using Deep Learning Techniques" explores the advancements in using deep learning algorithms for the analysis of MRI images to detect and diagnose Alzheimer's Disease (AD). It highlights various methodologies that leverage Convolutional Neural Networks (CNNs) and other machine learning approaches to identify structural brain changes associated with AD. The review discusses the effectiveness of different model architectures, including ResNet and enhancing diagnostic accuracy. It also emphasizes the importance of preprocessing techniques that improve image quality and model performance. Furthermore, it examines the challenges in obtaining large, labeled datasets for training deep learning models and the need for robust evaluation metrics. By synthesizing findings from multiple studies, the review underscores the potential of deep learning to transform Alzheimer's diagnosis and monitoring. The authors conclude that integrating these advanced techniques can lead to earlier detection and better patient management strategies. Overall, this review contributes to the growing body of knowledge on AI applications in neuroimaging. The review discusses preprocessing methods that enhance image quality and model performance while addressing challenges like the need for large annotated datasets. Ultimately, the paper emphasizes the potential of deep learning to improve diagnostic accuracy.

Key Points

- Increased diagnostic precision through advanced deep learning methodologies applied to MRI analysis.
- Timely detection of Alzheimer's Disease enables better patient management and intervention strategies.
- Valuable insights into various approaches support ongoing research and development in neuroimaging applications.

2.3 Taha H. Rassem, Suhad Al-Shoukry, Nasrin Makbol.," Alzheimer's Diseases Detection by Using Deep Learning Algorithms: A Mini-Review.," 2023.

Alzheimer's Disease Detection by Using Deep Learning Algorithms provides an overview of the application of deep learning algorithms in the detection of Alzheimer’s Disease (AD). The review highlights the significance of utilizing machine learning techniques, particularly Convolutional Neural Networks (CNNs), to analyze medical imaging data and identify patterns associated with AD. It discusses various deep learning architectures and their effectiveness in improving diagnostic accuracy. The author also emphasizes the role of preprocessing steps in enhancing image quality, which is crucial for accurate model predictions. Additionally, the paper addresses challenges such as data scarcity and the need for comprehensive datasets to train robust models. And summarizes recent advancements and trends in the field, indicating the growing importance of artificial intelligence in neuroimaging. By compiling findings from various studies, the review serves as a valuable resource for researchers exploring deep learning applications in Alzheimer's detection. The author concludes that further research is essential for optimizing these algorithms and integrating them into clinical practice.

Deep learning techniques for detecting Alzheimer’s Disease, focusing on their effectiveness in identifying subtle brain changes. It emphasizes the importance of high-quality imaging data and serves as a resource for integrating artificial intelligence into clinical practice guiding future efforts in integrating artificial intelligence into the diagnosis and management of Alzheimer’s Disease.

Key Points

- Alzheimer, emphasizing their effectiveness in identifying subtle brain changes.
- It highlights the importance of high-quality medical imaging data and preprocessing methods to enhance the performance of deep learning models.
- The review serves as a resource for researchers and guiding future efforts integrating into the diagnosis and management of Alzheimer’s Diseases.

2.4 Seung Kyu Kim, Quan Anh Duong, Jin Gham.,"Multimodal 3D Deep Learning for Early Diagnosis of Alzheimer’s" 2023.

Multimodal 3D deep learning is a promising approach for the early diagnosis of Alzheimer’s disease, utilizing advanced machine learning techniques to analyze multiple types of data. It combines structural brain imaging (like MRI), functional imaging (such as PET scans), genetic data, and cognitive assessments to provide a comprehensive analysis of the brain. This fusion of diverse data sources allows the deep learning model to detect subtle patterns and early biomarkers that are often missed by traditional methods.

3D convolutional neural networks (CNNs) play a key role in this process by analyzing volumetric brain images, capturing spatial relationships and structural changes in brain regions such as the hippocampus, which are affected early in Alzheimer’s. These models can be trained on labeled datasets, allowing them to predict the onset of Alzheimer’s years before symptoms like memory loss or cognitive decline become apparent. 3D deep learning is applied for early Alzheimer’s disease detection by analyzing brain imaging data, such as MRI and PET scans. These models detect subtle structural changes in regions like the hippocampus, which are early indicators of Alzheimer’s. By integrating multimodal data, including genetic and cognitive information, the models can predict the onset of the disease before significant symptoms appear, improving early diagnosis and potential interventions. Using 3D convolutional neural networks (CNNs), the model processes brain images to detect subtle changes that signal early signs of Alzheimer's.

Key Points

- Detects subtle brain changes in early stages through 3D analysis of MRI and PET scans.
- Integrates multiple data sources (imaging, genetic, cognitive) for more accurate predictions.

2.5 Abdul Rehmen, Abdul Majeed.," Early Diagnosis of Alzheimer's Disease Using 18F-FDG PET With Soften Latent Representation." 2023.

The early diagnosis of Alzheimer's disease using 18F-FDG PET imaging focuses on assessing glucose metabolism in the brain, which typically declines in individuals with the disease. This technique involves administering a radioactive glucose tracer, allowing for the visualization of metabolic activity in various brain regions. A critical advancement in this area is the use of soften latent representation, which enhances the analysis of PET data by smoothing out noise and variability in the imaging results. By applying deep learning techniques to the PET scans, the model extracts latent features that represent underlying patterns of brain activity associated with Alzheimer's. The softening process reduces the complexity of these representations, making it easier to identify early metabolic changes that may indicate the onset of the disease. This is crucial because early detection significantly improves the potential for timely intervention and management, potentially delaying cognitive decline.

The combination of 18F-FDG PET with soften latent representation enhances diagnostic accuracy by integrating information across different brain regions, providing a more comprehensive view of metabolic health. This methodology allows clinicians to differentiate between normal aging and early Alzheimer's, leading to more targeted treatment strategies. Overall, this approach represents a significant advancement in neuroimaging techniques, offering hope for better outcomes in the fight against Alzheimer's disease by enabling earlier diagnosis and intervention.

Key Points

- Enhances early detection of Alzheimer's by identifying subtle metabolic changes in brain activity through 18F-FDG PET imaging.
- Improves diagnostic accuracy by using soften latent representation to reduce noise and variability in imaging data.

2.6 M. Folstein, Myung-Kyu Yi, Raza., " Clinical diagnosis of Alzheimer’s disease." 2022.

Clinical diagnosis of Alzheimer’s disease involves a comprehensive assessment that combines medical history, cognitive testing, and neuroimaging to accurately identify the condition. The process typically begins with a thorough evaluation of the patient’s symptoms, including memory loss, confusion, and changes in behavior or personality. Physicians may conduct standardized cognitive assessments to evaluate memory, attention, language, and problem-solving skills, helping to establish the degree of cognitive impairment.

Additionally, a detailed medical history is crucial, as it includes information about the patient's family history of Alzheimer’s and any relevant medical conditions or medications that might affect cognitive function. Physical examinations and laboratory tests may also be performed to rule out other potential causes of dementia-like symptoms, such as vitamin deficiencies or thyroid disorders. Neuroimaging techniques, such as MRI and CT scans, play a vital role in the clinical diagnosis by identifying structural brain changes associated with Alzheimer’s, such as atrophy in the hippocampus. In some cases, PET scans using tracers like 18F-FDG can provide insights into brain metabolism, revealing areas of reduced activity typical in Alzheimer’s patients. The clinical diagnosis is often supported by the application of diagnostic criteria established by organizations such as the National Institute on Aging and the Alzheimer’s Association, which outline specific requirements for diagnosing Alzheimer’s disease. Importantly, clinical diagnosis is usually a multi-disciplinary effort, involving neurologists, psychiatrists, and neuropsychologists to ensure a comprehensive evaluation.

Key Points

- Provides a comprehensive assessment combining cognitive testing, medical history, and neuroimaging for accurate diagnosis.
- Helps rule out other potential causes of cognitive impairment, ensuring a focused Alzheimer’s diagnosis.

2.7 V. Masurkar, R. Kaur, G. Bawa.," Generalizable deep learning model for early Alzheimer’s disease detection from structural MRIs." 2022.

A generalizable deep learning model for early Alzheimer’s disease detection from structural MRIs is designed to identify the disease at its earliest stages by analyzing brain anatomy through MRI scans. Structural MRIs provide detailed images of the brain’s key regions, such as the hippocampus and cortex, which are among the first areas to show signs of degeneration in Alzheimer’s. The model uses convolutional neural networks (CNNs) to automatically extract features from these MRI scans, identifying subtle patterns of brain atrophy that may be difficult for traditional diagnostic methods to detect.

Early detection is critical in Alzheimer’s disease because it allows for timely intervention, which can slow the progression of symptoms and improve the patient’s quality of life. This deep learning model excels in identifying early structural changes in the brain, even before noticeable cognitive decline occurs, making it a valuable tool for screening high-risk individuals or those with mild cognitive impairment. Furthermore, the model’s adaptability means it can be integrated with other forms of data, such as genetic information or cognitive assessments, enhancing its diagnostic accuracy. It improves patient outcomes by enabling earlier diagnosis and timely intervention. Its ability to process large volumes of MRI data quickly and efficiently also makes it scalable for widespread use in clinical settings, helping healthcare providers detect Alzheimer’s in a larger patient population.

Key Points

- Detects early brain atrophy from MRIs, enabling diagnosis before significant cognitive decline.
- Generalizable across diverse populations and MRI datasets, adaptable to various clinical settings.
- Automates feature extraction, increasing efficiency and scalability in detecting Alzheimer’s disease.

2.8 R. Kushol, Y. N. Surendran, V. Sugukar, " Alzheimer's disease detection from structural MRI using fusion transformer." 2022.

Alzheimer's disease detection using structural MRI and a fusion transformer model combines the strengths of transformers and feature fusion to improve diagnostic accuracy. Transformers, known for their powerful attention mechanisms, can efficiently capture global dependencies across MRI slices, allowing the model to focus on the most relevant brain regions affected by Alzheimer's. Feature fusion integrates multi-scale spatial features from different layers or modalities, such as cortical thickness and hippocampal atrophy, to create a richer representation of brain structure. This fusion enables the model to capture both fine-grained local details and broader contextual information, enhancing early detection capabilities.

Unlike traditional CNNs, fusion transformers offer better long-range spatial attention and can dynamically weigh important features, improving sensitivity to subtle changes in brain anatomy. This architecture can handle high-dimensional MRI data while being adaptable to different MRI acquisition protocols. Additionally, by utilizing pre-trained models and fine-tuning on specific Alzheimer's datasets, the model can achieve higher accuracy with fewer labeled samples. The fusion transformer's ability to generalize across diverse datasets also addresses challenges of variability in MRI scans. Overall, this approach presents a cutting-edge solution for early, accurate, and robust Alzheimer's disease diagnosis.

Key Points

- Fusion transformers capture both local and global brain features, enhancing sensitivity to subtle Alzheimer's-related changes.
- Fusion transformers capture both local and global brain features, enhancing sensitivity to subtle Alzheimer's-related changes.
- Pre-training and feature fusion reduce the need for large labeled datasets, making the model more efficient.

2.9 N.B. Romdhane, Y. Zhang, F. Shabbir.," "Deep learning-based Alzheimer's disease prediction for smart health system"." 2022.

Deep Learning-based Alzheimer's Disease Prediction for Smart Health System focuses on integrating advanced deep learning techniques into smart health systems to enhance early detection and monitoring of Alzheimer's disease. It emphasizes the importance of using machine learning algorithms to analyze complex healthcare data, particularly neuroimaging and clinical metrics, to identify early signs of Alzheimer's. The study discusses the use of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to process MRI scans and time-series data from electronic health records (EHRs). By leveraging these deep learning models, the researchers aim to improve the predictive accuracy of Alzheimer's diagnoses compared to traditional methods.

Additionally, Deep learning based Alzheimer disease detection highlights the benefits of using a smart health system, which includes real-time monitoring and the ability to adapt to individual patient profiles. This adaptability is crucial for personalized treatment plans. The researchers also address challenges such as data privacy and the need for robust training datasets that represent diverse populations to avoid biases in prediction. Challenges of variability in MRI scans. Overall, this approach presents a cutting-edge solution for early, accurate, and robust Alzheimer's disease diagnosis.

Key Points

- The integration into smart health systems allows for real-time monitoring and personalized treatment plans tailored to individual patient profiles.
- Utilizing diverse datasets mitigates bias in predictions, promoting equitable healthcare outcomes across different populations.
- Deep learning enhances predictive accuracy for Alzheimer's disease by analyzing complex imaging and more effectively than traditional methods.

2.10 Suhuai Luo, J. Chen, T. Zhao, "A Survey on Alzheimer's Disease Prediction Using Deep Learning". 2021.

A Survey on Alzheimer's Disease Prediction Using Deep Learning provides a comprehensive overview of various deep learning methodologies applied to the prediction and diagnosis of Alzheimer's disease. The authors review several key approaches, emphasizing the importance of early detection for effective intervention and treatment planning. The survey categorizes existing studies based on the types of data used, including neuroimaging (like MRI and PET scans), genetic data, and clinical assessments. It highlights the effectiveness of convolutional neural networks (CNNs) for image analysis and recurrent neural networks (RNNs) for sequential data processing. The review also discusses the integration of multi-modal data sources, which enhances predictive accuracy by combining imaging, biomarker, and clinical information. evaluate the strengths and weaknesses of different deep learning architectures, addressing challenges such as data imbalance, overfitting, and the need for large annotated datasets. They stress the significance of transfer learning in utilizing pre-trained models to improve performance.

Moreover, the paper outlines future research directions, including the development of more interpretable models to understand the decision-making process of deep learning systems better. It calls for more standardized protocols in data collection and processing to facilitate comparability among studies.

Key Points

- Deep learning models enhance predictive accuracy for Alzheimer's disease by effectively analyzing complex neuroimaging and clinical data.
- Integration of multi-modal data sources allows for a comprehensive understanding of disease progression and improves early detection capabilities.
- Transfer learning enables the use of pre-trained models, reducing the need for extensive labeled datasets while maintaining performance.

CHAPTER 3

SYSTEM ARCHITECTURE

3.1 EXISTING SYSTEM

In the existing system for Alzheimer's syndrome recognition using deep learning, medical professionals typically rely on a combination of brain imaging, cognitive tests, and biomarker analysis to diagnose the disease. Traditional methods include using to detect physical changes in the brain, such as shrinkage in areas like the hippocampus, which is crucial for memory. Cognitive tests, such as the Mini-Mental State Examination (MMSE), help assess the patient’s memory, thinking, and reasoning abilities. Biomarkers, like amyloid-beta and tau proteins, can also be measured through cerebrospinal fluid or imaging to identify the buildup of abnormal proteins associated with Alzheimer's. Convolutional Neural Networks (CNNs), a popular deep learning model, are particularly good at analyzing brain images and identifying small changes that doctors may not detect. These models are trained using thousands of labeled brain scans, learning to distinguish between healthy brains and those affected by Alzheimer's. Some deep learning models are trained to classify brain images into categories (healthy, early-stage Alzheimer's, late-stage Alzheimer's) based on these patterns. People with Alzheimer's may experience symptoms such as memory loss, confusion about time and place, difficulty in completing familiar tasks, challenges in problem-solving, and changes in mood or personality. Early stages often involve subtle memory lapses, while later stages can lead to severe cognitive impairment, requiring assistance with basic activities. Some models can even predict how fast the disease will progress by analyzing brain images over time. Researchers have also combined deep learning with other data, such as genetic risk factors and cognitive test results, to make predictions more accurate. Despite the valuable information these traditional techniques provide, they often fall short in early detection. Alzheimer’s-related changes in the brain can be very subtle in the initial stages, and these minor alterations are challenging to detect with conventional imaging alone. This is where deep learning, a branch of artificial intelligence (AI), offers transformative potential. Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have the ability to sift through vast amounts of complex neuroimaging and genetic data, uncovering patterns associated with Alzheimer’s that may be imperceptible to the human eye. CNNs are especially adept at processing image data, identifying nuanced structural changes in the brain that may signal the early on set of Alzheimer's. These algorithms are trained on thousands of labeled brain scans to recognize distinctions between healthy brains and those impacted by Alzheimer's, thereby enabling them to classify brain images into categories such as healthy, early-stage, or advanced Alzheimer's. Beyond imaging, some advanced deep learning models incorporate other types of data, such as genetic markers APOE gene variants, for instance and results from cognitive tests. This multi-modal approach, which integrates multiple data sources, enhances the model’s predictive accuracy, paving the way for more reliable diagnoses. These systems can even be trained to predict the progression of Alzheimer’s by analyzing brain images over time, offering valuable insights into the likely course of the disease. CNNs are trained using vast datasets of labeled brain scans, learning to differentiate between healthy brains and those affected by Alzheimer’s. Through repeated exposure to labeled data, these models learn to recognize specific patterns that correlate with different stages of Alzheimer’s. They can classify brain images into categories such as healthy, early-stage Alzheimer’s, and late-stage Alzheimer’s based on these learned patterns. This automated pattern recognition makes CNNs especially valuable for early detection, as they can identify subtle structural changes that may otherwise go unnoticed by medical professionals. In addition to classification, some deep learning models are also trained to predict the progression of Alzheimer’s by analyzing changes in brain images over time. These models can observe the rate at which the disease advances, giving clinicians insights into how quickly cognitive function may decline in a particular patient. By tracking the disease’s progression, deep learning models offer a way to tailor interventions and plan for long-term care needs more effectively. Furthermore, researchers have been exploring ways to enhance deep learning systems for Alzheimer’s diagnosis by integrating multiple data sources. Combining neuroimaging with genetic information and cognitive test results, for instance, provides a multi-modal approach that gives a more comprehensive view of Alzheimer’s risk and progression. Genetic factors like the APOE gene, which is associated with a higher risk of Alzheimer’s, can contribute valuable information when combined with brain imaging and cognitive test scores. This multi-modal approach allows deep learning models to consider a range of Alzheimer’s-related factors, which can increase diagnostic accuracy and improve early detection.

Despite the advantages of deep learning in Alzheimer’s diagnosis, there are still significant challenges to overcome. One of the primary challenges is the need for large, high-quality datasets to train these models effectively. Deep learning algorithms require extensive data for accurate training, but acquiring a large, representative dataset of brain scans, genetic information, and cognitive assessments is difficult. Privacy concerns, data accessibility issues, and high costs make it challenging to gather such comprehensive datasets, limiting the potential of deep learning systems to reach their full diagnostic capability. This lack of transparency can be problematic for medical professionals, who may hesitate to trust results from a model that does not explain its decision-making process. Clinicians rely on clear reasoning to make informed decisions, and a system that lacks interpretability may not align with the clinical decision-making process, thus limiting its adoption. Despite these challenges, deep learning systems continue to make strides in Alzheimer’s research and diagnosis. Researchers are actively working on solutions to improve model transparency, such as using techniques to visualize which areas of the brain the model focuses on when making its predictions. These advancements aim to bridge the gap between deep learning models and clinical practice, making the models more accessible and interpretable for medical professionals. With ongoing improvements in deep learning technology and better access to diverse data, these systems offer promising support for clinicians in the fight against Alzheimer’s. By aiding in earlier and more accurate detection, deep learning models can contribute to better disease management and treatment planning. Early detection is especially valuable, as it allows for timely interventions that may slow the progression of Alzheimer’s, ultimately improving the patient’s quality of life. And this multi-modal approach enables the system to consider a range of factors, leading to more reliable and early diagnoses. Despite the advancements, the current deep learning systems still face challenges. The need for large, high-quality datasets to train these models is significant, and such data is not always easily accessible. Additionally, deep learning models are often seen as "black boxes" because they don’t explain how they reach their conclusions, making it harder for doctors to fully trust the results. Nonetheless, these systems are rapidly improving, helping medical professionals detect Alzheimer's earlier and more accurately, which is essential for better disease management and treatment planning. The existing system for Alzheimer’s recognition utilizes cognitive tests and biomarker analysis to determine whether the disease is present. Traditional methods may struggle with early detection, often leading to delayed diagnoses. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), enhance these assessments by identifying subtle patterns in cognitive data and integrating various sources for improved accuracy. Despite challenges like data access and model transparency, deep learning significantly advances diagnostic capabilities. Ultimately, this technology aids in accurately confirming or ruling out Alzheimer’s, facilitating better disease management and care.

3.1.1 DISADVANTAGES

- Traditional methods may miss early signs of Alzheimer’s, delaying recognition.
- Manual review of cognitive tests and biomarker data can introduce human error and bias.
- Inaccuracy which may not fully capture the disease's complexity or early indicators
- Dependence on clinician expertise and judgment.
- Lack of scalability.

3.2 PROPOSED SYSTEM

The proposed system for recognizing Alzheimer’s syndrome using deep learning aims to enhance early diagnosis and improve accuracy by leveraging advanced technology. This system will employ a multi-modal approach, integrating various data types such as brain scans (MRI and PET), genetic information, and cognitive test results. The proposed system for Alzheimer’s disease prediction uses deep learning and multimodal analysis, combining MRI scans, PET images, genetic data, and cognitive test results to improve early detection and diagnosis. By analyzing different types of medical data together, the system provides a complete and accurate assessment of a patient’s condition. The model is built using DenseNet and VGG-16, two deep learning algorithms that help identify brain structure changes linked to Alzheimer’s. DenseNet improves feature sharing between layers, making the model efficient, while VGG-16 captures important details in MRI and PET scans. The system first processes the images by resizing, normalizing, and applying small modifications like rotation and flipping to improve learning. A pre-trained DenseNet and VGG-16 model is then fine-tuned using transfer learning, helping it recognize patterns related to Alzheimer’s. These models detect brain shrinkage, changes in white matter, and memory-related regions, which are key indicators of Alzheimer’s. The system then classifies the scans and helps predict how the disease may progress over time. By combining different medical data sources, the model makes more accurate and reliable predictions. Doctors can use these predictions to create personalized treatment plans, improving patient care. The system’s accuracy is measured using metrics like accuracy, precision, and recall, ensuring it performs well. Since the system is scalable, it can be used in hospitals or cloud platforms for real-time automated diagnosis, reducing doctors' workload. The AI model helps in faster, more efficient Alzheimer’s detection, supporting early intervention. Future improvements may include new AI techniques like Vision Transformers, which can make predictions even more accurate. The system could also be linked to electronic health records (EHRs) to provide doctors with quick access to patient history. Using large amounts of medical data, the model can be trained to recognize Alzheimer’s in diverse patient groups worldwide. This AI-powered system represents an important step forward in medical diagnosis, helping detect Alzheimer’s earlier and improving patient outcomes.

The novelty of this project lies in its multimodal approach to Alzheimer’s disease detection, integrating MRI scans, PET images, genetic data, and cognitive test results for a more accurate and early diagnosis. It leverages advanced deep learning models, DenseNet and VGG-16, which enhance feature extraction and classification accuracy. DenseNet improves feature propagation, while VGG-16 effectively captures structural details in brain images. The system also uses transfer learning, reducing the need for large datasets and making the model more efficient and adaptable. One of the key innovations is its ability to predict disease progression, helping doctors personalize treatment plans based on the rate of cognitive decline. It also applies image enhancement techniques, such as normalization, resizing, and augmentation, ensuring better model performance. The system is scalable, meaning it can be deployed in hospitals or on cloud platforms for real-time automated analysis. Additionally, it ensures trust and transparency by providing explainable AI predictions, making it easier for doctors to interpret results. The model’s real-time processing allows for quick and accurate diagnosis, reducing reliance on highly skilled radiologists and making Alzheimer’s detection faster and more accessible. It has been evaluated using accuracy, precision, recall, and F1-score, ensuring high reliability. Moreover, this system can be extended to detect other neurodegenerative diseases, broadening its impact. By bridging the gap between technology and medicine, this AI-powered solution significantly improves early diagnosis, treatment planning, and patient outcomes, This project introduces an AI-driven multimodal system that integrates MRI, PET, and genetic data, utilizing DenseNet and VGG-16 for superior feature extraction and accurate Alzheimer’s detection. By leveraging transfer learning and real-time processing, the system ensures fast diagnosis, high accuracy, and scalability, making it suitable for both hospital and cloud-based deployment. A key innovation is its ability to predict disease progression, allowing doctors to personalize treatment plans and intervene at the right time for better patient outcomes. With explainable AI predictions and reduced dependency on expert radiologists, this system makes

Alzheimer’s detection more transparent, accessible, and efficient, ultimately improving early diagnosis and care.

This system can be further enhanced by integrating natural language processing (NLP) to analyze patient medical histories and doctor’s notes for deeper insights. Expanding the dataset with multi-center medical records will help improve the model’s generalization across different populations. Real-time monitoring through wearable health devices could also be incorporated, allowing for continuous tracking of cognitive decline. The integration of reinforcement learning can refine prediction accuracy by adapting to new patterns in brain imaging. Additionally, developing a user-friendly interface for clinicians will make it easier to interpret AI-generated reports. Cloud-based deployment can support remote diagnosis, making Alzheimer’s detection accessible even in rural or underdeveloped areas. Further advancements in explainable AI will enhance transparency, allowing doctors to understand the reasoning behind predictions. Incorporating genomic analysis could offer a more personalized approach by identifying genetic risk factors linked to Alzheimer’s. Collaborations with pharmaceutical researchers may also help in discovering new treatment strategies. Ultimately, this AI-driven system has the potential to revolutionize Alzheimer’s diagnosis and care, leading to improved patient outcomes and early intervention strategies.

In the future, the Alzheimer’s disease prediction system using multimodal analysis with DenseNet and VGG-16 can be enhanced in several ways. Integrating speech and text analysis from patient interactions could help detect early cognitive decline. Expanding the model with larger datasets from different hospitals and demographics will improve accuracy and generalization. A cloud-based platform can support remote diagnosis, making the system accessible to people in rural areas. Explainable AI (XAI) can be integrated to help doctors understand how the model makes decisions, increasing trust in AI-based predictions. Combining DenseNet and VGG-16 with reinforcement learning will refine model performance by adapting to new patterns in brain imaging. Genetic data and biomarker analysis can be incorporated to personalize Alzheimer’s risk assessment. A user-friendly interface for clinicians can simplify AI-based decision-making, making it easier to use in hospitals. Collaborating with neurologists and researchers can lead to improved Alzheimer's treatment strategies.

METHODOLOGY

The methodology for Alzheimer's disease prediction using multimodal analysis and DenseNet begins with the collection of MRI scans, PET images, genetic data, and cognitive test results from both healthy individuals and Alzheimer's patients. This diverse dataset ensures a comprehensive representation of disease progression across different patient groups. Preprocessing techniques such as image resizing, normalization, and data augmentation (rotation, flipping, contrast adjustments) are applied to standardize images, improving the model's ability to generalize across varied data sources. DenseNet, a deep learning model known for its efficient feature propagation, is fine-tuned using transfer learning to extract complex structural patterns from MRI and PET images. The multimodal fusion process combines outputs from DenseNet with additional medical data like genetic markers and cognitive scores, integrating different sources for a more holistic prediction of Alzheimer's disease.

The extracted features are processed through Dense layers, refining classification into healthy and Alzheimer's-affected groups. The model is trained using cross-entropy loss and optimized using the Adam optimizer, ensuring stable learning while dropout regularization prevents overfitting. The system's performance is evaluated using metrics like accuracy, precision, recall, and F1-score to assess predictive reliability across different patient conditions. Cloud deployment allows for real-time automated analysis, making Alzheimer's diagnosis more accessible and scalable. This multimodal approach, powered by DenseNet, enhances early detection, disease monitoring, and personalized treatment planning, significantly improving Alzheimer's patient care. Data preprocessing steps include resizing and normalizing images to fit the input dimensions of DenseNet and VGG16 models, with standardization to align pixel values, enhancing model stability and performance.

MRI and PET images for Alzheimer's prediction. It combines advanced deep learning techniques with interpretability features, aiming to offer an accurate, scalable, and early- stage diagnostic tool for Alzheimer's disease. The proposed system for Alzheimer's disease prediction uses deep learning models, specifically DenseNet, VGG16, and Dense layers, applied to MRI and PET imaging for improved diagnosis accuracy. Starting with data acquisition and preprocessing, MRI and PET scans are resized, normalized, and augmented to enhance model robustness. DenseNet and VGG16 serve as backbone models, each optimized for feature extraction. DenseNet's residual connections effectively capture detailed brain features, while VGG16's uniform layers focus on structural changes. After processing through these models, Dense layers are added for multi-class classification into healthy, early-stage, or late-stage Alzheimer's. Combining DenseNet and VGG16 enhances diagnostic precision, especially when differentiating between Alzheimer's stages. Training optimizes the model with cross-entropy loss and the Adam optimizer, using dropout regularization to prevent overfitting. Evaluation includes metrics like accuracy, precision, recall, F1-score, to assess the model's predictive performance across all stages of Alzheimer's. The system's scalability allows deployment on hospital servers or cloud platforms, enabling real-time, automated analysis for large patient volumes, reducing reliance on skilled personnel and expediting diagnosis. Despite challenges like high-quality data requirements and model interpretability, this system's integration of deep learning for Alzheimer's prediction holds potential to transform diagnostic workflows, providing timely, accurate predictions that support proactive care and better patient outcomes.

3.2.1 ADVANTAGES

- Automated brain image detection and classification.
- Robust and adaptable deep learning framework.
- Utilizes a robust framework capable of process diverse data for precise analysis.
- Improved accuracy in identifying signs of Alzheimer's.
- Leverages multiple imaging techniques (MRI, PET) to improve the sensitivity of early Alzheimer's detection.

3.3 SYSTEM DIAGRAM

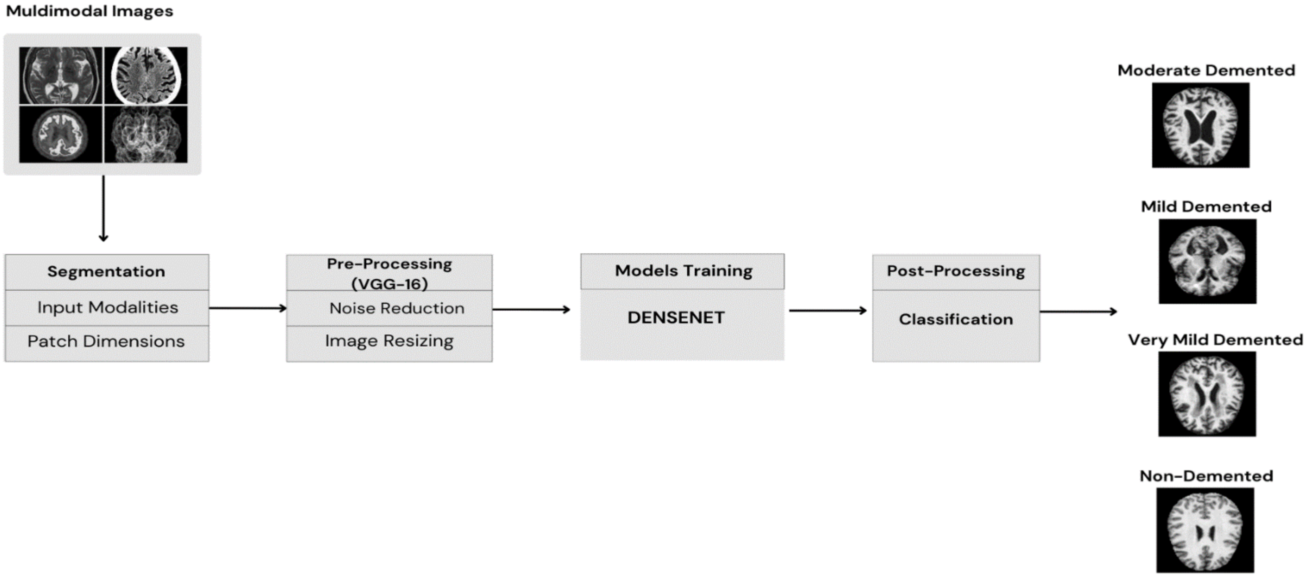

FIG 3.3 SYSTEM DIAGRAM

3.1.1 USE CASE DIAGRAM

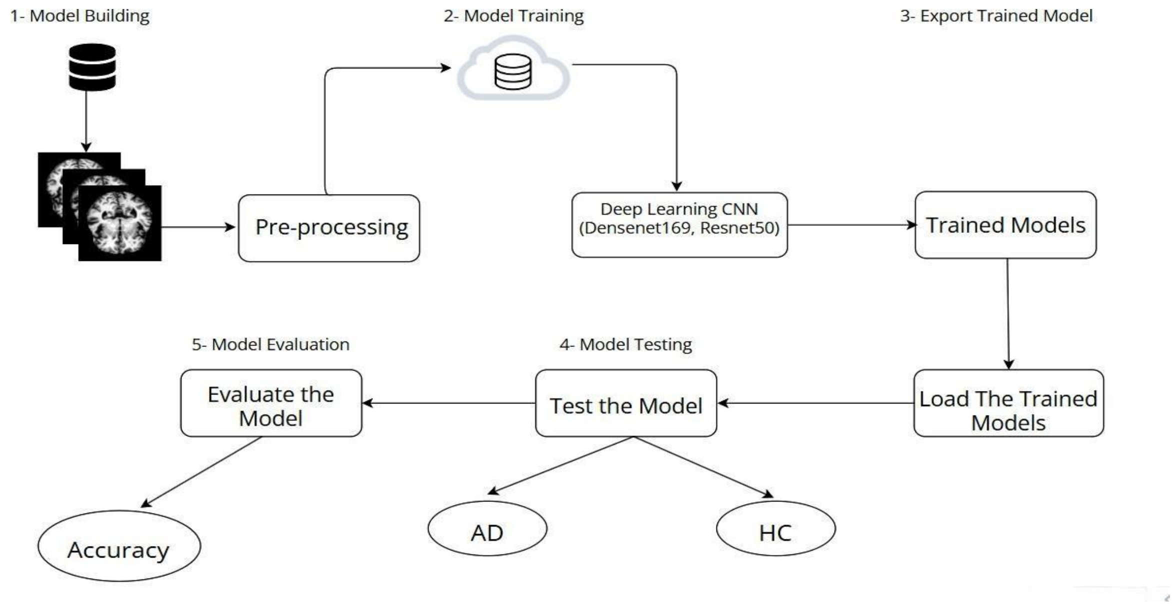

FIG 3.1.1 USE CASE DIAGRAM

3.1.2 CLASS DIAGRAM

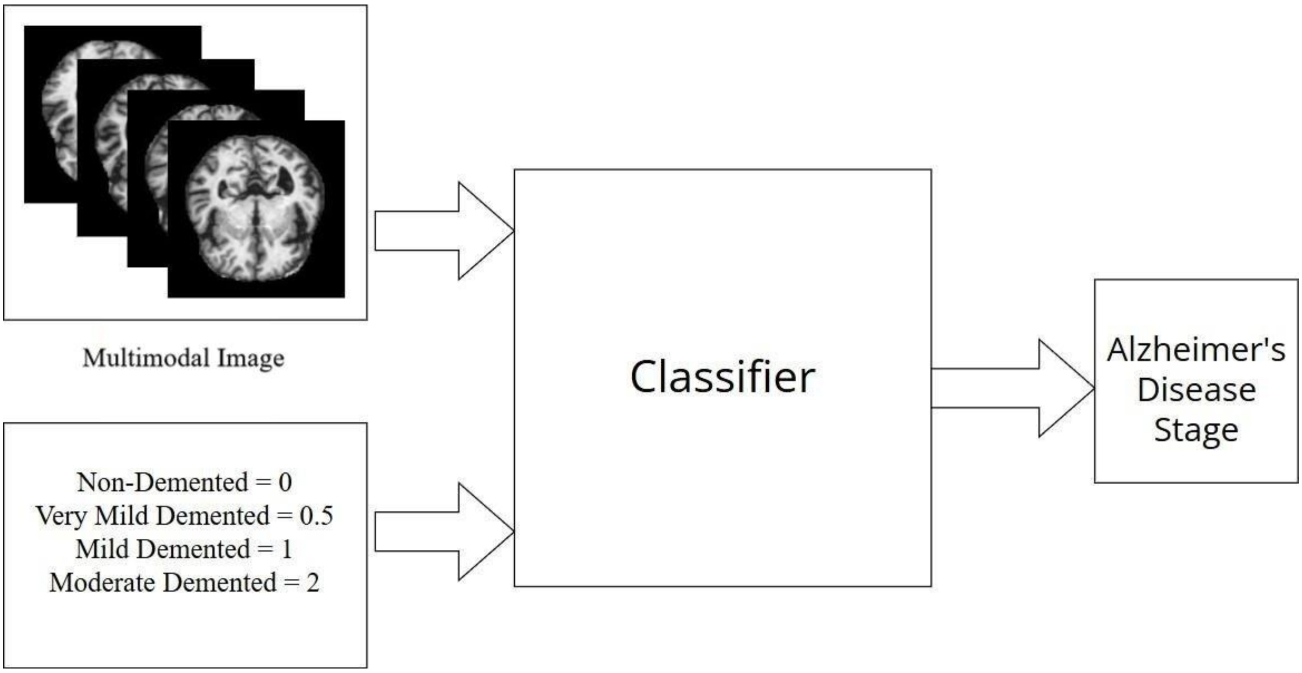

Fig 3.1.2 CLASS DIAGRAM

3.1.3 FLOW DIAGRAM

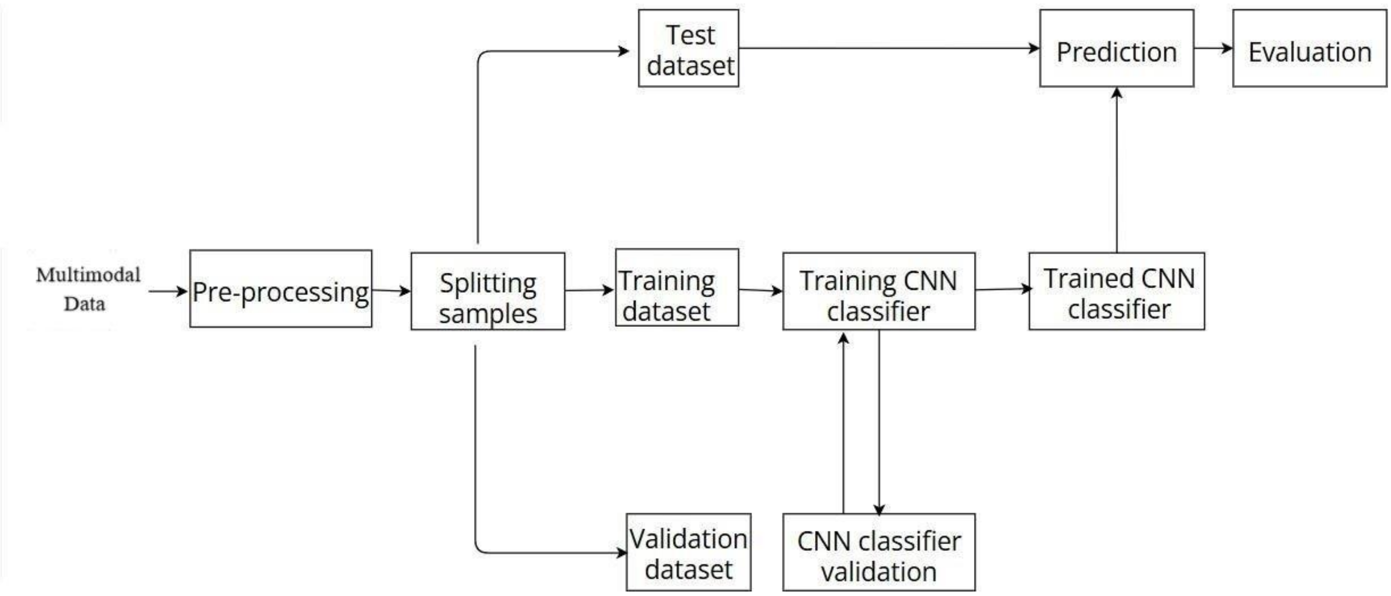

Fig 3.1.3 FLOW DIAGRAM

3.1.4 SEQUENCE DIAGRAM

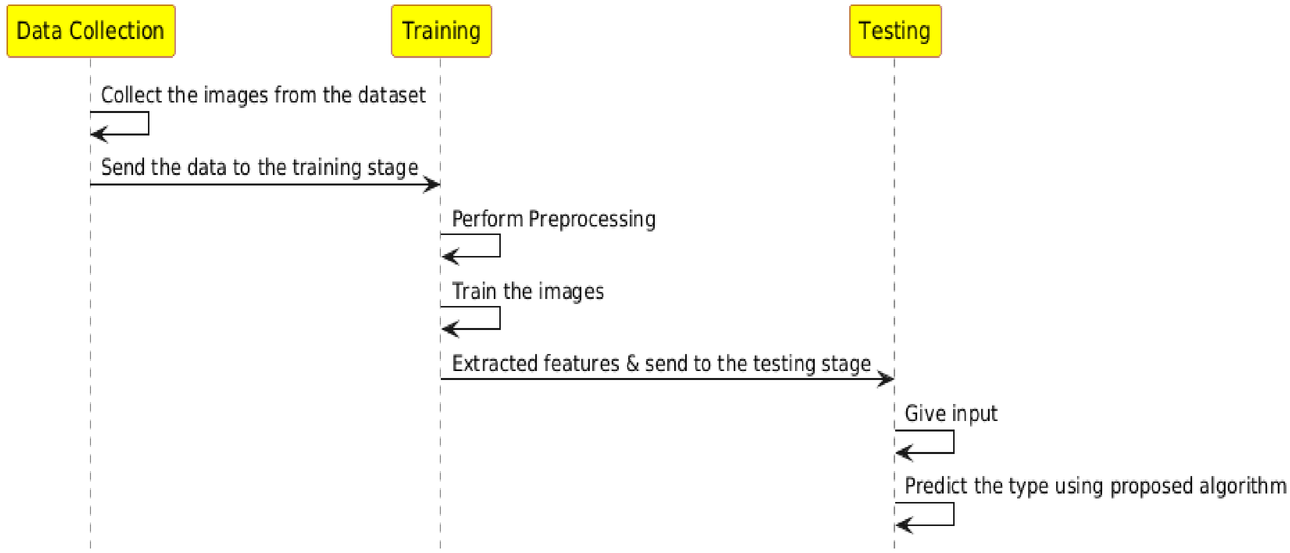

FIG 3.1.4 SEQUENCE DIAGRAM

3.1.5 ACTIVITY DIAGRAM

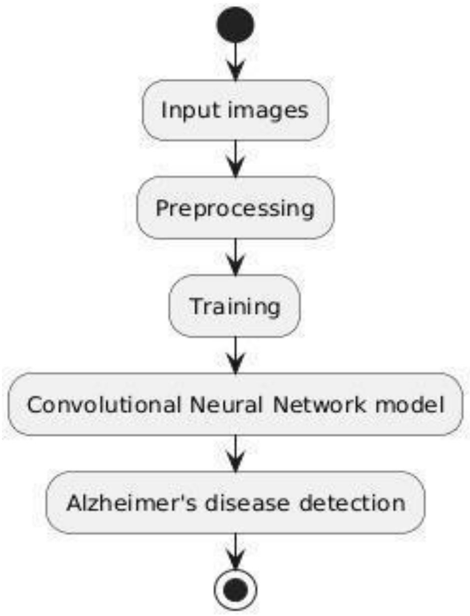

FIG 3.1.5 ACTIVITY DIAGRAM

CHAPTER 4

SYSTEM REQUIREMENTS

4.1 HARDWARE REQUIREMENTS

- **System** : Basic laptop or desktop with internet connectivity.
- **GPU** : NVIDIA RTX 3080 with at least 10GB VRAM.
- **Hard Disk** : At least 1TB SSD for fast data retrieval and storage.
- **Mouse** : Standard Mouse.
- **Keyboard** : Standard Keyboard.
- **RAM** : 32GB minimum.

4.2 SOFTWARE REQUIREMENTS

- **Operating System** : Windows 10/11.
- **DL Frameworks** : TensorFlow, PyTorch, Keras.
- **Visualization Tools** : Matplotlib, Seaborn, TensorBoard.
- **Data Preprocessing** : Tensorflow.
- **Development Tool** : Jupter NoteBook.

HARDWARE DESCRIPTION

GPU

- **NVIDIA RTX** : The NVIDIA RTX series, particularly with its powerful GPU capabilities, enhances the performance of deep learning models used in Alzheimer's research by accelerating image processing and neural network training.

SOFTWARE DESCRIPTION

DL Frameworks

- **TensorFlow** : TensorFlow aids in Alzheimer's prediction by supporting deep learning models that analyze brain scans, genetics, and biomarkers to detect early disease signs. TensorFlow handles large datasets efficiently, allowing for scalable model training. This helps researchers develop tools for early diagnosis and tracking disease progression.

- **PyTorch** : PyTorch aids Alzheimer's prediction by supporting CNN models that analyze MRI and PET scans to detect disease markers. While transfer learning fine-tunes pre-trained models on specific datasets. This approach enhances early diagnosis and tracking of Alzheimer's progression.
- **Keras** : Keras helps predict Alzheimer's by enabling CNN models to analyze MRI scans for early disease signs. Its simple API supports rapid model building and testing, while transfer learning optimizes pre-trained models for specific datasets. This enhances early diagnosis and monitoring of Alzheimer's progression.

Visualization Tools

- **Matplotlib** : Matplotlib aids Alzheimer's prediction by visualizing data like brain scan images, training accuracy, and model loss. It helps researchers interpret model outcomes and analyze patterns linked to disease progression.
- **Seaborn** : Seaborn is used in Alzheimer's prediction to create informative visualizations that help analyze relationships between various biomarkers and disease progression. It provides enhanced statistical graphics, such as heatmaps and pair plots, to identify patte rns and correlations in datasets related to Alzheimer's.
- **TensorBoard** : TensorBoard is used in Alzheimer's prediction to visualize model training metrics, such as loss and accuracy over time, facilitating performance analysis. It also helps in visualizing complex neural network architectures.

Data Preprocessing

- **Tensorflow** : In Alzheimer's prediction, TensorFlow is utilized for preprocessing tasks like normalizing and augmenting medical imaging data to enhance model training and improve prediction accuracy.

CHAPTER 5

SYSTEM IMPLEMENTATION

5.1 MODULES

- Data Acquisition Module
- Data preprocessing
- Early Detection and Diagnosis
- Multimodal Analysis

5.2 MODULES DESCRIPTION

5.2.1 Data Acquisition Module

- The Data Acquisition Module is responsible for collecting and storing various types of data relevant to Alzheimer's disease prediction. This includes medical imaging data, such as MRI or CT scans, alongside demographic and clinical patient information. The module ensures secure storage of this data, allowing for efficient retrieval and management during analysis.
- The Data Acquisition Module gathers diverse types of data essential for predicting Alzheimer’s disease. It focuses on collecting medical imaging data, such as MRI and PET scans, along with cognitive assessment results and demographic details of patients. The module ensures that all collected data is accurate and complete through validation checks. It also maintains strict privacy standards to safeguard patient information. Furthermore, the data is organized with metadata tags, making it easy to retrieve specific records for analysis.

5.2.2 Data Preprocessing

- This module focuses on cleaning and transforming raw data into a suitable format for analysis. Key tasks include image processing techniques such as normalization, resizing, denoising, and augmentation of medical images. Additionally, it performs feature extraction to derive relevant metrics from imaging data and encodes categorical patient data into numerical formats for model input.

- The Data Preprocessing Module prepares raw data for analysis in Alzheimer’s disease prediction. It starts by fixing any missing or incorrect data to ensure everything is accurate. This module also standardizes the data formats, making sure everything is consistent across different datasets. It uses data augmentation techniques to create additional training examples, which helps improve the model’s performance. Additionally, the module scales and normalizes the data, making it ready for Deep Learning algorithms. By organizing and enhancing the data, this module boosts the accuracy of the prediction models.

5.2.3 Early Detection and Diagnosis

- Early detection and diagnosis of Alzheimer’s disease are crucial for effective treatment and management of the condition. Identifying the disease in its initial stages allows for timely interventions, which can help slow its progression and improve the quality of life for patients. Various methods are used for early diagnosis, including cognitive assessments, neuropsychological testing, and medical imaging techniques like MRI and PET scans. Biomarkers, such as amyloid and tau protein levels, are also analyzed through blood tests and cerebrospinal fluid samples to provide further insight. Advanced technologies, including machine learning algorithms, are increasingly employed to analyze patterns in imaging data and patient information, enhancing diagnostic accuracy.
- Alzheimer's can be detected in early stages through cognitive assessments, brain imaging, and biomarker analysis. Early diagnosis allows for timely intervention to slow the syndrome's progression. Public awareness and education about the early signs of Alzheimer’s are essential for encouraging individuals to seek medical advice sooner. Overall, a comprehensive approach to early detection significantly contributes to better outcomes for those affected by Alzheimer’s disease.

5.2.4 Multimodal Analysis

- Multimodal analysis helps predict Alzheimer’s disease (AD) by combining MRI/PET scans, genetic data, and clinical records for better accuracy. DenseNet, a deep learning model, processes these data types to find patterns linked to AD. The process includes data preparation, feature extraction, and classification to detect early signs of the disease. Datasets like ADNI and Kaggle help train the model, while accuracy and sensitivity measure its performance. Challenges include limited data, high costs, and making AI models more understandable. Future AI improvements can help in early diagnosis and better treatment planning. Additionally, advancements in transfer learning allow researchers to leverage pre- trained models on large datasets, reducing the need for extensive labeled data while still achieving high performance in Alzheimer’s prediction tasks.
- Moreover, the integration of multimodal data, including PET scans and genetic information, into deep learning frameworks provides a more comprehensive view of the disease, allowing for better predictive capabilities. Overall, deep learning is revolutionizing Alzheimer’s disease prediction by enabling earlier detection and more precise assessments of disease progression.
- Deep learning models and AI are being used to predict Alzheimer's based on multimodal data like brain scans, genetic tests, and biomarkers. Early prediction aids in proactive disease management and tailored treatment plans. The use of explainable AI techniques is also becoming prominent, providing insights into how models make predictions and increasing trust among clinicians. Overall, these technological improvements not only enhance prediction accuracy but also pave the way for more personalized approaches to Alzheimer's care and treatment.

CHAPTER 6

RESULT

Sample Outputs

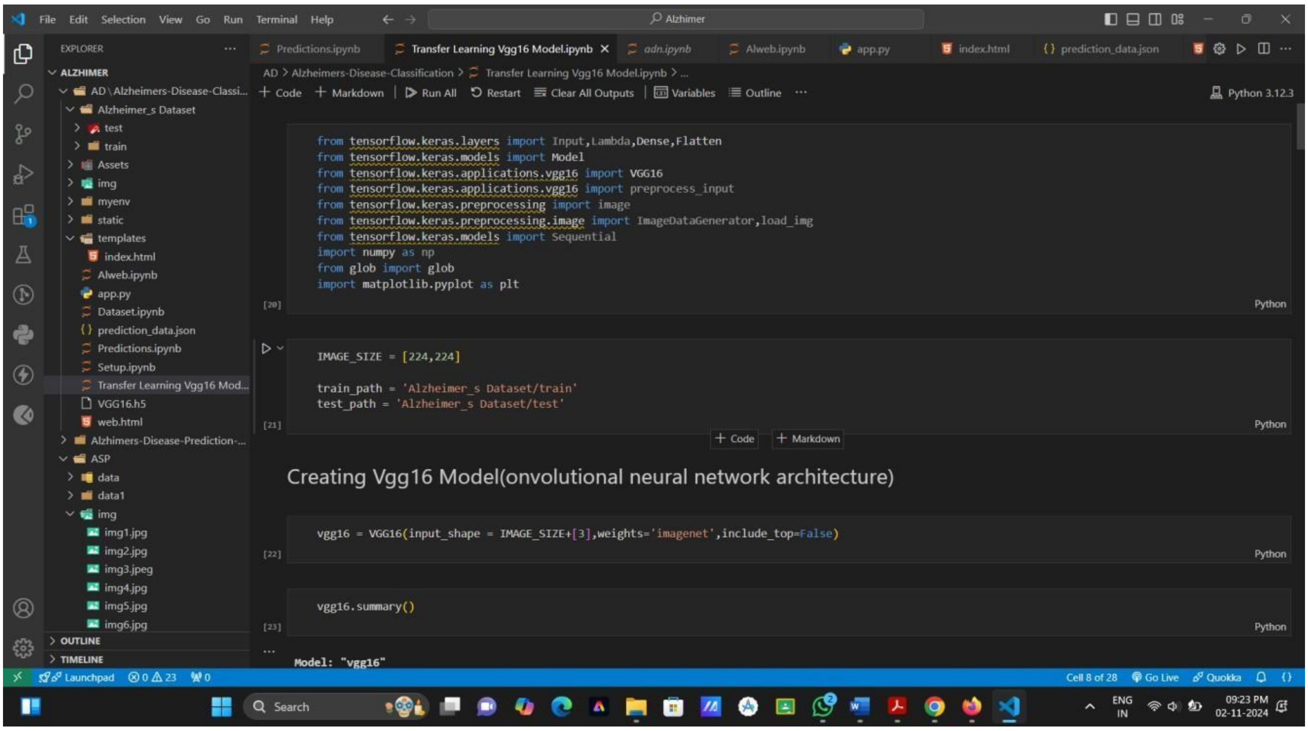

Fig 6.1 Starting Page

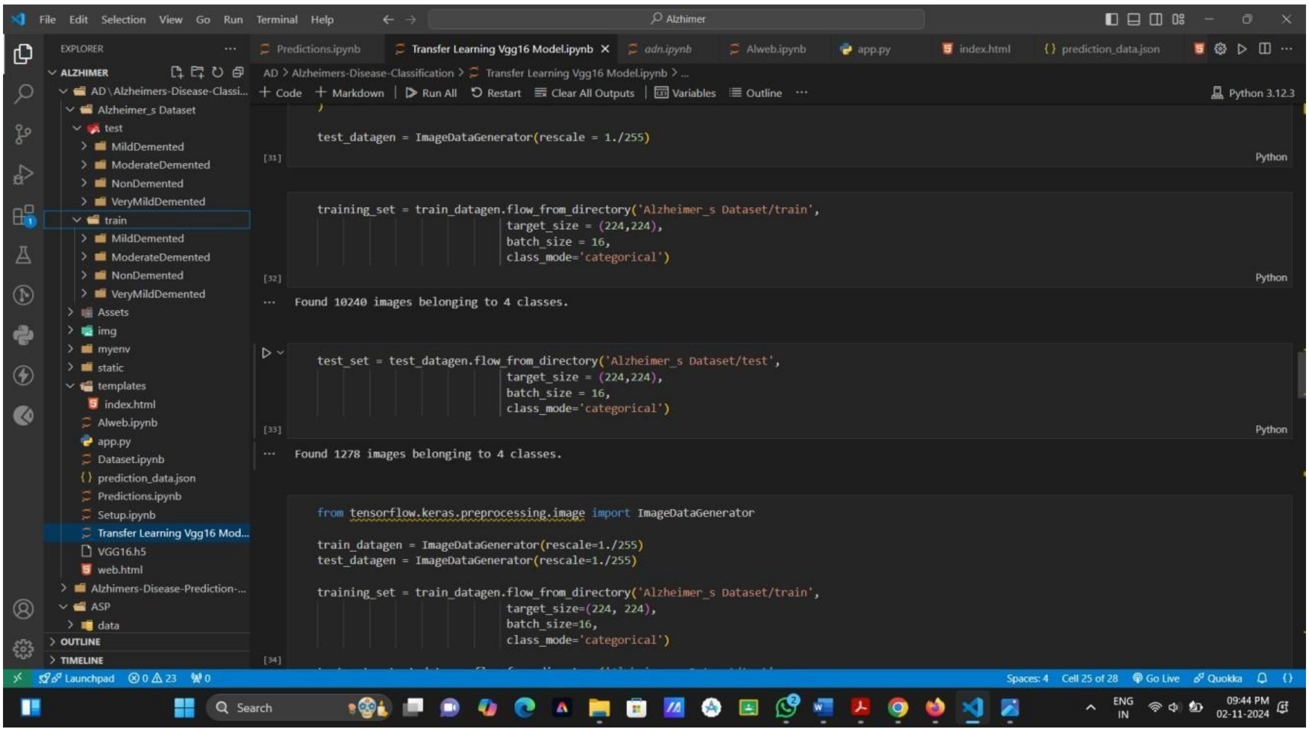

Fig 6.2 Test and Train Set

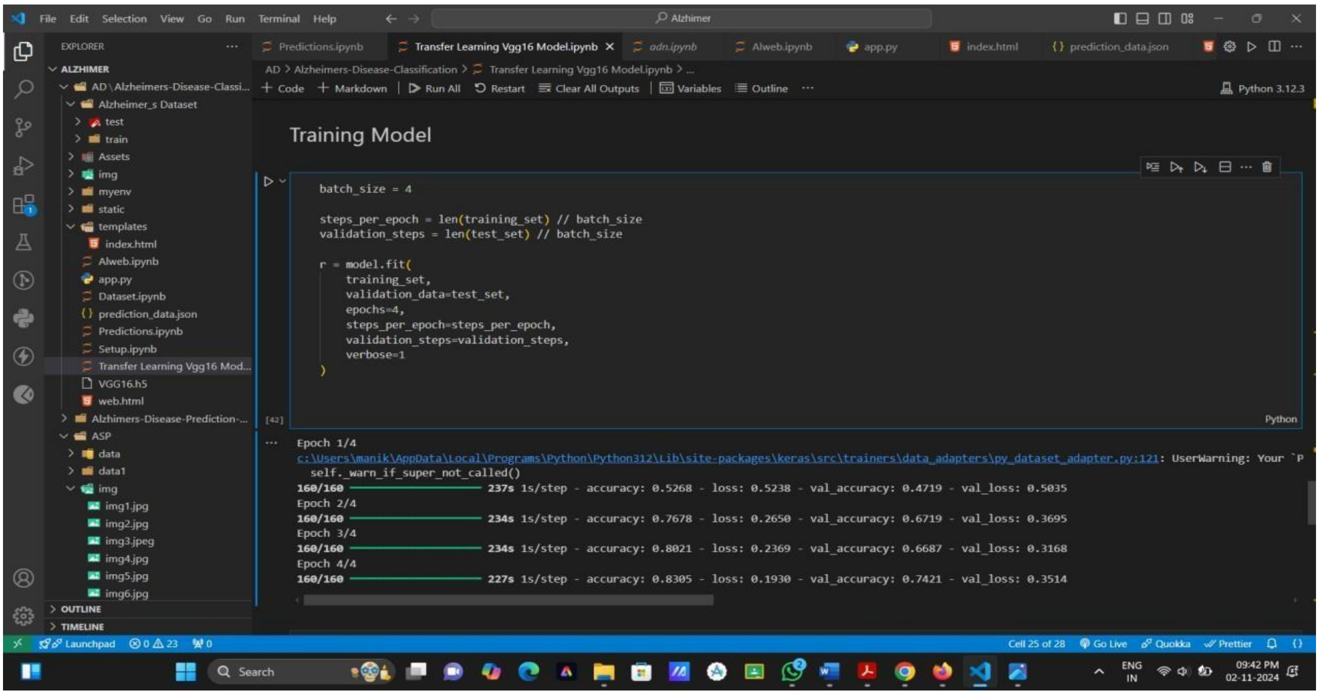

Fig 6.3 Train Model

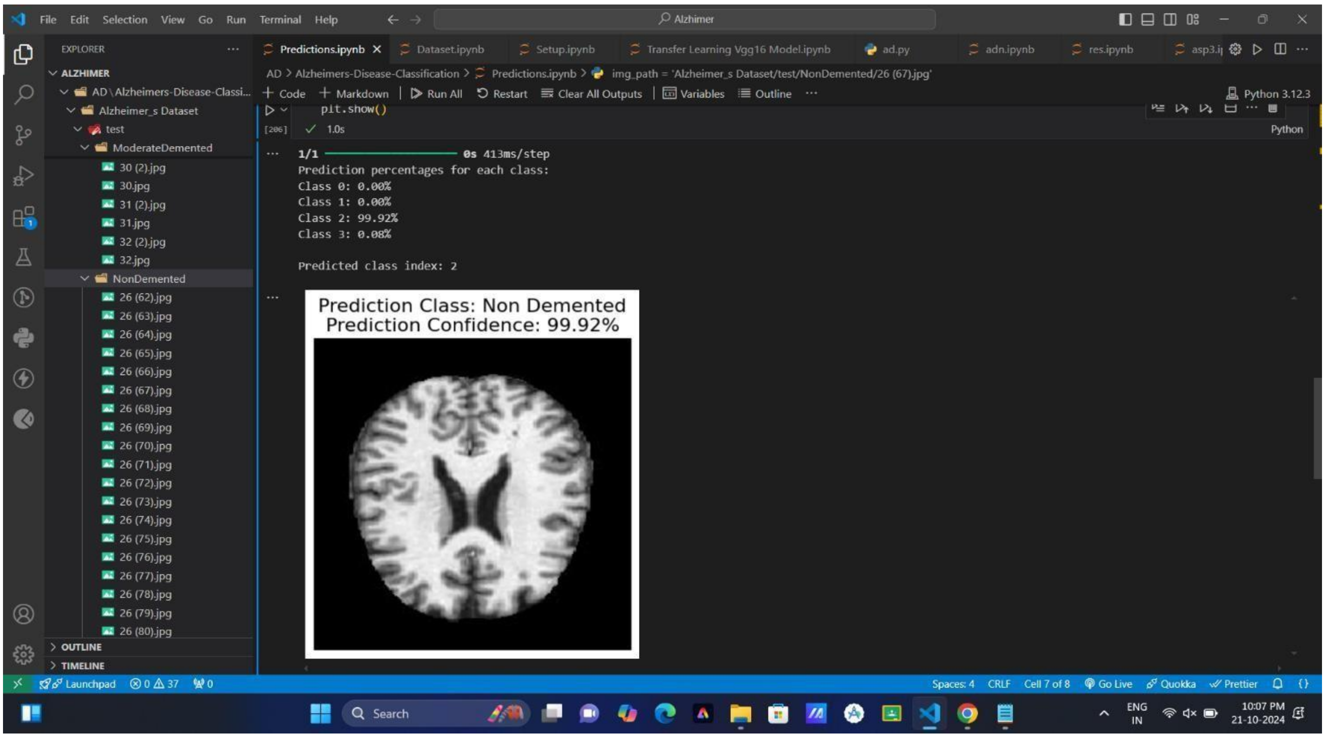

Fig 6.4 Non Demented AD Prediction

Non-demented refers to no Alzheimer's disease occurs.

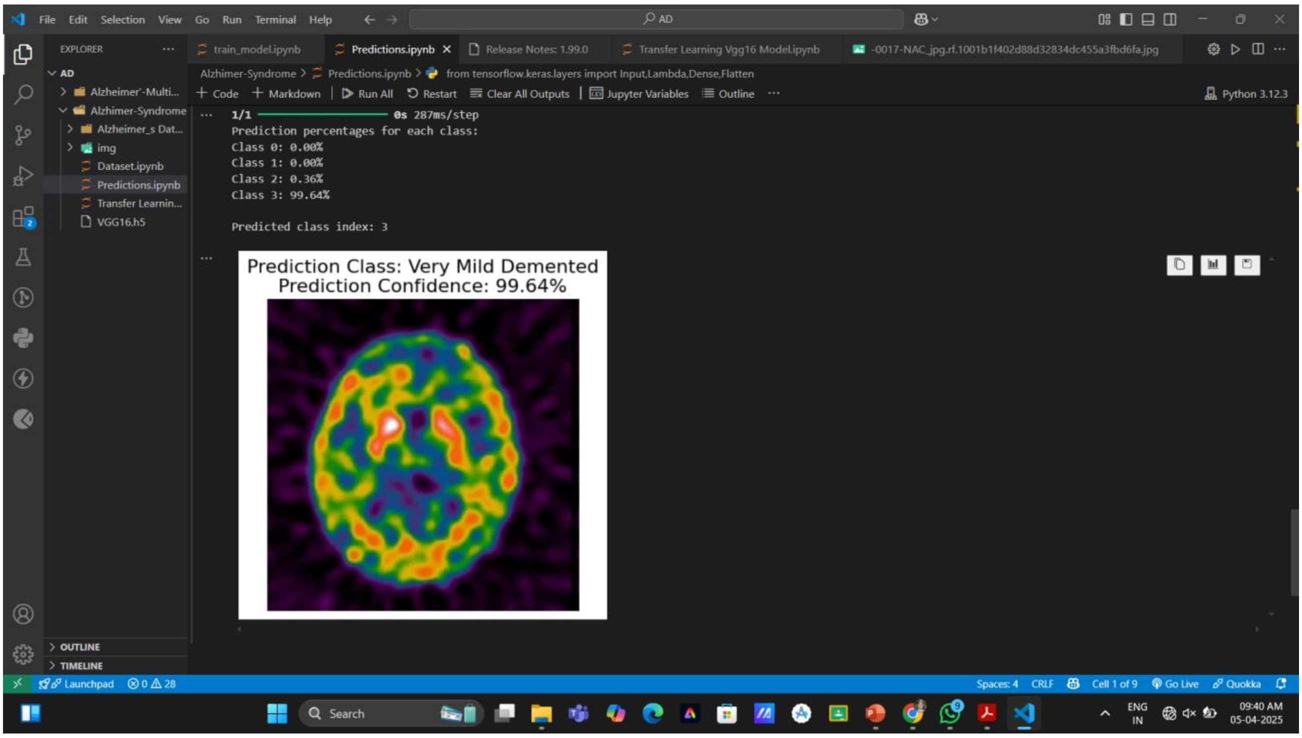

Fig 6.5 Very Mild Demented AD Prediction

Very mild Alzheimer's refers to the initial stage predicted with 88.32% accuracy.

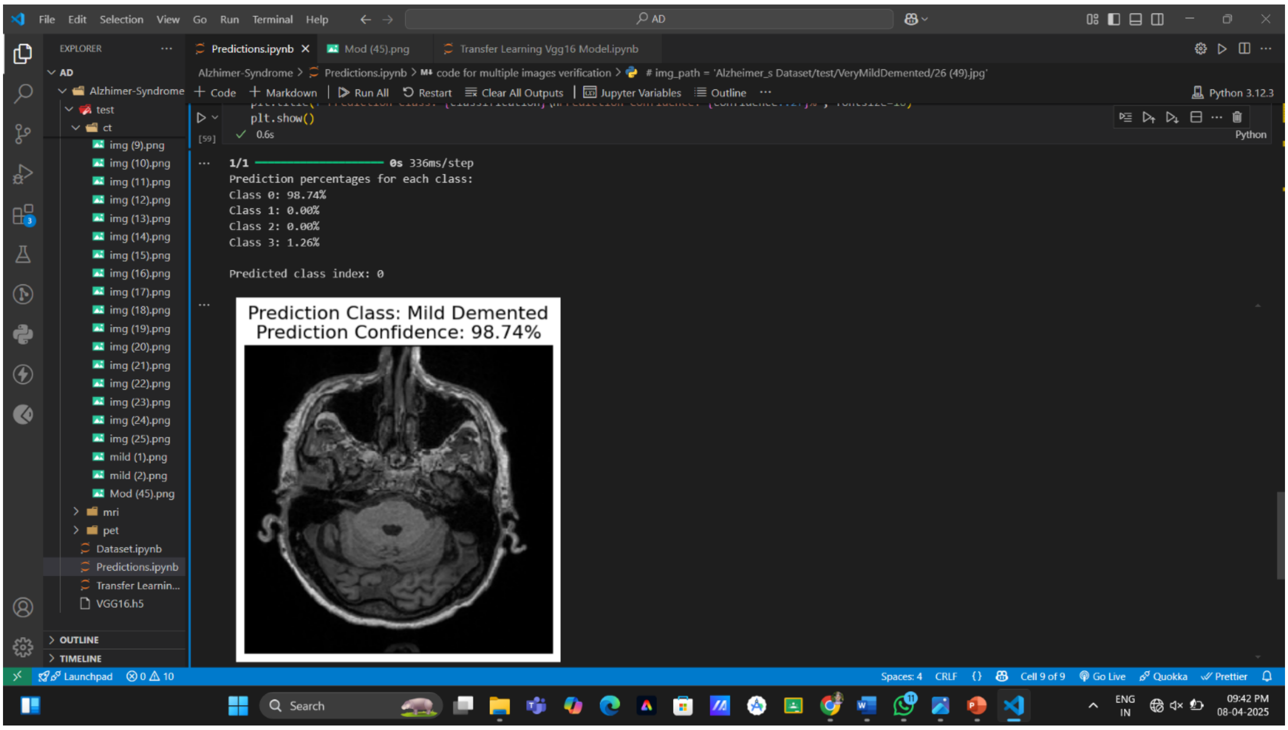

Fig 6.6 Mild Demented AD Prediction

Mild Demented refers to the Middle stage predicted with 75.05 % accuracy.

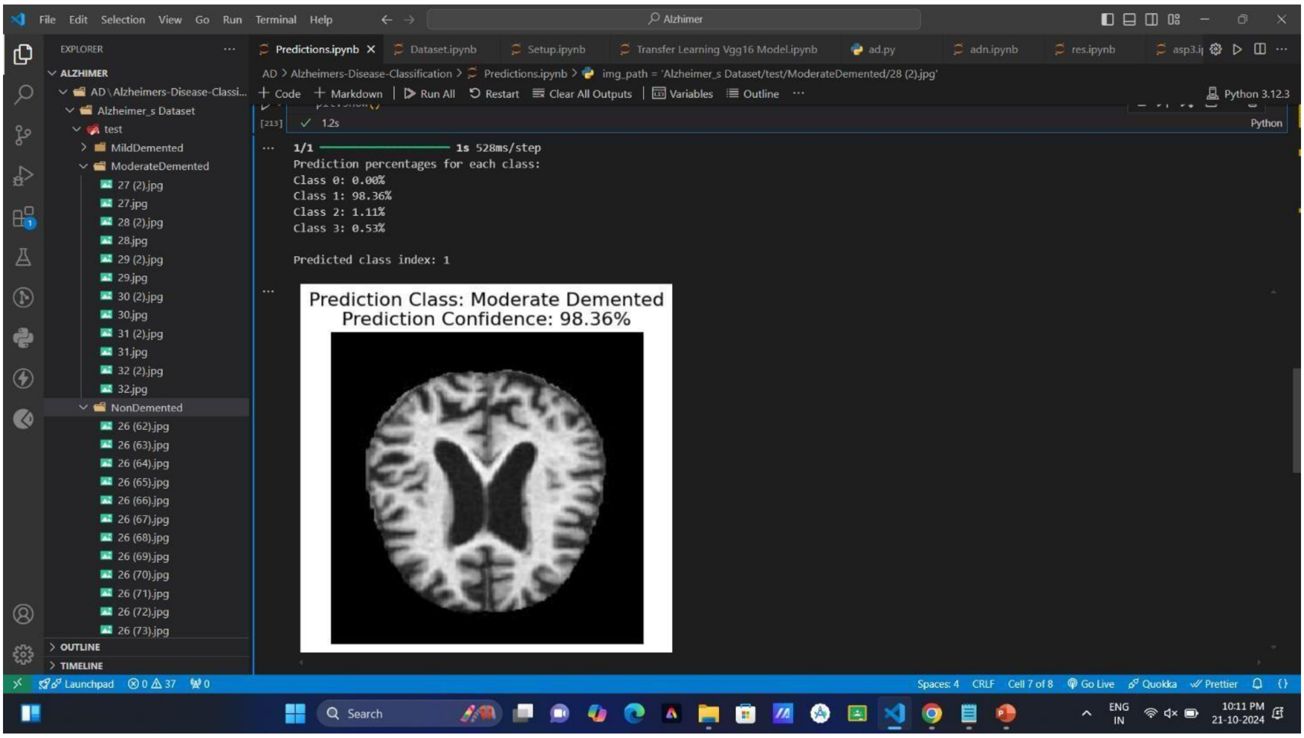

Fig 6.7 Moderate Demented AD Prediction

Moderate Alzheimer's is often referred to as the "final stage" with almost complete dependency, predicted with 98.36 % accuracy

CHAPTER 7

PROJECT OUTCOMES


VELAMMAL
INSTITUTE OF TECHNOLOGY
Chennai - Kolkatta Highway, Panchetti, Ponneri

5th International Conference on Artificial Intelligence,

6G Communications and Network Technologies - ICA6NT 2025

Certificate of Appreciation

This is to certify that

MANOJKUMAR K

P.S.R. Engineering College, Sivakasi

has participated and presented paper entitled

Advanced Deep Learning Framework for Alzheimer's Syndrome Recognition using Resnet Based Architecture

at the **5th International Conference on Artificial Intelligence, 6G Communications and Network Technologies (ICA6NT 2025)** organized by the **Department of Electronics and Communication Engineering**, **Velammal Institute of Technology,** Chennai held on **27th & 28th , March 2025.**

Coordinator	Coordinator	Coordinator	Convener	Conference Chair
Dr.R.Jothi Chitra	Dr. M. Sivarathinabala	Mr. K. Ragupathi	Dr. B. Sridevi	Dr. N. Balaji
Professor-ECE	Professor-ECE	Assistant Professor-ECE	Professor & Head -ECE	Principal

CHAPTER 8
CONCLUSION

In conclusion, deep learning models like DenseNet and VGG-16 have shown remarkable potential in predicting Alzheimer's disease through multimodal analysis. DenseNet are effective in extracting spatial features from brain imaging data such as MRI and PET scans, capturing patterns that indicate early signs of the disease. DenseNet, an advanced form of enhances feature learning by introducing dense connections between layers, which improves gradient flow, feature reuse, and overall model efficiency. These models can detect subtle abnormalities in brain structure that are often missed by traditional methods. When combined with additional data such as genetic information and cognitive test scores, this multimodal approach significantly improves prediction accuracy. Despite challenges like limited datasets, data heterogeneity, and high computational requirements, the integration of DenseNet within a multimodal framework offers better generalization and performance. To make these models clinically useful, improving interpretability and ensuring consistent data quality are essential. Future research should also explore techniques like transfer learning and data augmentation to overcome data limitations. Overall, using DenseNet in multimodal deep learning brings us closer to accurate, early, and non-invasive diagnosis of Alzheimer's disease, representing a promising advancement in the field of medical AI. Overall, DenseNet in multimodal frameworks are powerful tools in advancing Alzheimer's diagnosis and care. More research and better data will improve the results even further. In the future, this method can really help in fighting Alzheimer's disease. It brings us closer to faster and more accurate diagnosis.

CHAPTER 9

APPENDIX

Sample Coding

```
from tensorflow.keras.layers import Input,Lambda,Dense,Flatten
from tensorflow.keras.models import Model
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.applications.vgg16 import preprocess_input
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import
ImageDataGenerator,load_img
from tensorflow.keras.models import Sequential
import numpy as np
from glob import glob
import matplotlib.pyplot as plt
IMAGE_SIZE = [224,224]
train_path = 'Alzheimer_s Dataset/train'
test_path = 'Alzheimer_s Dataset/test'
vgg16 = VGG16(input_shape =
IMAGE_SIZE+[3],weights='imagenet',include_top=False)
vgg16.summary()
for layer in vgg16.layers:
layer.trainable= False
folder = glob('Alzheimer_s Dataset/train/*')
folder
x = Flatten()(vgg16.output)
prediction = Dense(4,activation='softmax')(x)
model = Model(inputs=vgg16.input , outputs=prediction)
model.summary()
model.compile(
loss='categorical_crossentropy',
optimizer='adam',
metrics=['accuracy'],
)
from tensorflow.keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(
rescale = 1./255,
shear_range = 0.2,
```

```
zoom_range = 0.2,
horizontal_flip = True
)
test_datagen = ImageDataGenerator(rescale = 1./255)
training_set = train_datagen.flow_from_directory('Alzheimer_s Dataset/train',
 target_size = (224,224),
 batch_size = 16,
 class_mode='categorical')
test_set = test_datagen.flow_from_directory('Alzheimer_s Dataset/test',
target_size = (224,224),
batch_size = 16,
class_mode='categorical')
from tensorflow.keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)
training_set = train_datagen.flow_from_directory('Alzheimer_s Dataset/train',
target_size=(224, 224),
batch_size=16,
class_mode='categorical')
test_set = test_datagen.flow_from_directory('Alzheimer_s Dataset/test',
target_size=(224, 224),
batch_size=16,
class_mode='categorical')
print(len(training_set))
print(len(test_set))
model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])
# Define batch size
batch_size = 32  # or any desired batch size
# Print the lengths of training and test sets
print(len(training_set), len(test_set))
# Calculate steps per epoch and validation steps
steps_per_epoch = len(training_set) // batch_size
validation_steps = len(test_set) // batch_size
# Adjust to ensure rounding up when needed
steps_per_epoch = (len(training_set) + batch_size - 1) // batch_size
validation_steps = (len(test_set) + batch_size - 1) // batch_size
```

```
#ResNet Code
from tensorflow.keras import layers, Model
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.optimizers import Adam
base_model = ResNet50(weights='imagenet', include_top=False,
input_shape=(224, 224, 3))
for layer in base_model.layers:
layer.trainable = False
x = base_model.output
x = layers.GlobalAveragePooling2D()(x)
x = layers.Dense(1024, activation='relu')(x)
x = layers.Dropout(0.5)(x)
x = layers.Dense(512, activation='relu')(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(plt.rcParams["figure.figsize"] = [12.50, 5.50]
plt.rcParams["figure.autolayout"] = True
figure, axis = plt.subplots(1, 1)
plt.plot(r.history['loss'],label='train loss')
plt.plot(r.history['val_loss'],label='val loss')
plt.plot(r.history['accuracy'],label='train acc')
plt.plot(r.history['val_accuracy'],label='val acc')
plt.legend()
plt.show()
4, activation='softmax')(x)
batch_size = 4
steps_per_epoch = len(training_set) // batch_size
validation_steps = len(test_set) // batch_size
r = model.fit(
training_set,
validation_data=test_set,
epochs=4,
steps_per_epoch=steps_per_epoch,
validation_steps=validation_steps,
verbose=1
)
from tensorflow.keras.models import load_model
model = load_model('VGG16.h5')
```

```
from tensorflow.keras.layers import Input,Lambda,Dense,Flatten
from tensorflow.keras.models import Model
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.applications.resnet50 import preprocess_input
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import
ImageDataGenerator,load_img
from tensorflow.keras.models import Sequential
import numpy as np
from glob import glob
import matplotlib.pyplot as plt
import cv2
from tensorflow.keras.applications import VGG16
from tensorflow.keras import layers, models
base_model = VGG16(weights='imagenet', include_top=False,
input_shape=(224, 224, 3))
model = models.Sequential()
model.add(base_model)
model.add(layers.Flatten())
model.add(layers.Dense(4, activation='softmax'))
model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])
from tensorflow.keras.models import load_model
model = load_model('VGG16.h5')
img_path = 'Alzheimer_s Dataset/test/VeryMildDemented/26 (49).jpg'
img = load_img(img_path,target_size = (224,224))
x = image.img_to_array(img)
x=x/255
x.shape
img = x.reshape((1,224,224,3))
img.shape
ans = model.predict(img).argmax()
ans
# img_path = 'Alzheimer_s Dataset/test/VeryMildDemented/26 (49).jpg'
# img_path = 'Alzheimer_s Dataset/train/NonDemented/NoImpairment (20).jpg'
img_path = 'Alzheimer_s Dataset/test/MildDemented/27 (11).jpg'
# img_path = 'Alzheimer_s Dataset/test/ModerateDemented/29 (2).jpg'
# img_path = 'img/img10.jpg'
```

```
img = load_img(img_path, target_size=(224, 224))
x = image.img_to_array(img)
x = x / 255
img = x.reshape((1, 224, 224, 3))
prediction = model.predict(img)[0]
prediction_percentages = prediction * 100
ans = prediction.argmax()
print("Prediction percentages for each class:")
for i, percentage in enumerate(prediction_percentages):
print(f"Class {i}: {percentage:.2f}%")
print(f"\nPredicted class index: {ans}")
classifications = ["Mild Demented", "Moderate Demented", "Non Demented",
"Very Mild Demented"]
classification = classifications[ans]
confidence = prediction_percentages[ans]
sorted_indices = np.argsort(prediction_percentages)[::-1]
second_highest_class = classifications[sorted_indices[1]]
second_highest_confidence = prediction_percentages[sorted_indices[1]]
img = img.squeeze()
plt.imshow(img)
plt.axis('off')
plt.title(f"Prediction Class: {classification}\nPrediction Confidence:
{confidence:.2f}%", fontsize=16)
plt.show()
```

CHAPTER 10
REFERENCES

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