

NEURODETECT
AN AI-POWERED DEMENTIA PREDICTING SYSTEM

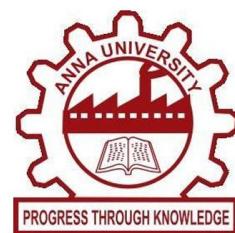
PROJECT PHASE I REPORT

Submitted by

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In partial fulfilment for the award of the degree of

BACHELOR OF TECHNOLOGY IN
ARTIFICIAL INTELLIGENCE AND DATA SCIENCE



RAJALAKSHMI ENGINEERING COLLEGE (AUTONOMOUS)

ANNA UNIVERSITY, CHENNAI – 602 105

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BONAFIDE CERTIFICATE

Certified that this report titled “**NEURODETECT: AN AI-POWERED DEMENTIA PREDICTING SYSTEM**” is the bonafide work of **GEETHA G (2116221801011)** and **SHANMUGASHREE M (2116221801049)** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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INTERNAL EXAMINER

EXTERNAL EXAMINER

DEPARTMENT VISION

To become a global leader in Artificial Intelligence and Data Science by achieving through excellence in teaching, training, and research, to serve the society.

DEPARTMENT MISSION

To develop students' skills in innovation, problem-solving, and professionalism through the guidance of well-trained faculty.

- To encourage research activities among students and faculty members to address the evolving challenges of industry and society.
- To impart qualities such as moral and ethical values, along with a commitment to lifelong learning

PROGRAMME EDUCATIONAL OBJECTIVES (PEOs)

PEO 1: Build a successful professional career across industry, government, and academia by leveraging technology to develop innovative solutions for real-world problems.

PEO 2: Maintain a learning mindset to continuously enhance knowledge through experience, formal education, and informal learning opportunities.

PEO 3: Demonstrate an ethical attitude while excelling in communication, management, teamwork, and leadership skills

PEO 4: Utilize engineering, problem-solving, and critical thinking skills to drive social, economic, and sustainable impact.

PROGRAM OUTCOMES (POs)

Engineering Graduates will be able to:

PO1: Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals and an engineering specialization to the solution of complex engineering problems.

PO2: Problem Analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

PO3: Design / Development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

PO4: Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO5: Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

PO6: The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

PO7: Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

PO8: Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO9: Individual and team work: Function effectively as an individual and as a member or leader in diverse teams, and in multidisciplinary settings.

PO10: Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11: Project management and finance: Demonstrate knowledge and understanding of the engineering management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

PO12: Life-long learning: Recognize the need for and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change

PROGRAM SPECIFIC OUTCOMES (PSOs)

A graduate of the Artificial Intelligence and Data Science Learning Program will demonstrate

PSO 1: Foundation Skills: Apply the principles of artificial intelligence and data science by leveraging problem-solving skills, inference, perception, knowledge representation, and learning techniques

PSO 2: Problem-Solving Skills: Apply engineering principles and AI models to solve real-world problems across domains, delivering cutting-edge solutions through innovative ideas and methodologies

PSO 3: Successful Progression: Utilize interdisciplinary knowledge to identify problems and develop solutions, a passion for advanced studies, innovative career pathways to evolve as an ethically responsible artificial intelligence and data science professional, with a commitment to society.

COURSE OBJECTIVE

- To identify and formulate real-world problems that can be solved using Artificial Intelligence and Data Science techniques.
- To apply theoretical and practical knowledge of AI & DS for designing innovative, data-driven solutions.
- To integrate various tools, frameworks, and algorithms to develop, test, and validate AI & DS models.
- To demonstrate effective teamwork, project management, and communication skills through collaborative project execution.
- To instill awareness of ethical, societal, and environmental considerations in the design and deployment of intelligent systems.

COURSE OUTCOME

CO 1: Analyze and define a real-world problem by identifying key challenges, project requirements and constraints.

CO 2: Conduct a thorough literature review to evaluate existing solutions, identify research gaps and formulate research questions.

CO 3: Develop a detailed project plan by defining objectives, setting timelines, and identifying key deliverables to guide the implementation process.

CO 4: Design and implement a prototype or initial model based on the proposed solution framework using appropriate AI tools and technologies.

CO 5: Demonstrate teamwork, communication, and project management skills by preparing and presenting a well-structured project proposal and initial implementation results.

CO-PO-PSO Mapping

CO	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12	PSO 1	PSO 2	PSO 3
CO 1	3	3	2	1	1	2	1	1	1	2	1	1	3	2	2
CO 2	2	3	1	3	1	1	1	1	2	2	2	3	2	2	2
CO 3	1	2	3	2	2	3	1	1	2	1	2	1	2	3	3
CO 4	3	2	3	2	3	1	1	2	1	1	1	2	3	3	3
CO 5	2	2	1	2	1	2	1	3	3	3	2	3	2	2	3

Note: Correlation levels 1, 2 or 3 are as defined below

1: Slight (Low) 2: Moderate (Medium) 3: Substantial (High)

No correlation: “-”

ABSTRACT

Dementia, a progressive neurodegenerative disorder, is one of the leading causes of disability and dependency among older adults worldwide. Early detection of dementia is crucial, as it enables timely clinical intervention, reduces disease progression, and improves patient quality of life. However, traditional diagnostic methods—such as neuropsychological tests and brain imaging—are often expensive, time-consuming, and inaccessible in low-resource environments. This project proposes an AI-powered early-stage dementia detection tool that leverages speech, behavioral, and cognitive data to identify subtle indicators of cognitive decline. Using techniques like MFCC extraction, Whisper-based ASR, and ensemble machine learning classifiers, the system analyzes linguistic and acoustic features, cognitive task performance, and behavioral responses to generate a personalized dementia risk score. Designed as a low-cost, non-invasive, multilingual, and user-friendly digital solution for mobile and web platforms, it enables continuous monitoring and tracking of cognitive trends, thereby democratizing dementia screening and bridging the gap between clinical diagnostics and community-based preventive healthcare.

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CHAPTER 1

INTRODUCTION

1.1 GENERAL

Dementia refers to a group of neurological disorders characterized by a decline in memory, reasoning, and cognitive abilities severe enough to interfere with daily functioning. According to the World Health Organization (WHO), more than 55 million people worldwide live with dementia, with nearly 10 million new cases each year. Alzheimer's disease is the most common form, contributing to 60–70% of cases.

The early stages of dementia are often subtle and easily overlooked, as patients may only show minor forgetfulness or language difficulties. Traditional diagnostic methods, including neuroimaging and clinical assessments, are accurate but costly, time-consuming, and require specialized medical personnel. As a result, many individuals remain undiagnosed until the disease has significantly progressed. This delay in diagnosis reduces the effectiveness of potential treatment and rehabilitation measures.

Artificial Intelligence (AI) has recently emerged as a transformative technology in healthcare diagnostics. With advancements in speech recognition, machine learning, and cognitive analytics, AI can detect hidden patterns in voice, language, and behavior that may indicate early cognitive impairment. These capabilities can help develop a low-cost and scalable screening tool suitable for real-world deployment.

1.2 NEED FOR THE STUDY

Early detection of dementia has profound implications for both individuals and society. As global life expectancy increases, the prevalence of dementia is projected to triple by 2050, posing significant socioeconomic and healthcare challenges. Traditional diagnosis often occurs only after noticeable cognitive decline, by which time therapeutic interventions have limited effectiveness.

There is, therefore, an urgent need for non-invasive, low-cost, and accessible screening methods that can identify early signs of cognitive decline without requiring clinical visits or expensive imaging. AI-driven models can fill this gap by analyzing everyday behavioral data—such as speech patterns and cognitive task performance—to predict dementia risk with high precision.

This study aims to contribute to the early detection and prevention of dementia through an innovative AI system that integrates multimodal data, continuous monitoring,

and multilingual capabilities. By democratizing cognitive health screening, it bridges the gap between advanced medical diagnostics and everyday accessibility, supporting healthcare providers, caregivers, and patients in early intervention planning.

1.3 OVERVIEW OF THE PROJECT

The proposed project, AI Tool for Early-Stage Dementia Detection, is designed to identify early symptoms of dementia through multimodal AI-based analysis. The system captures and processes speech, behavioral patterns, and cognitive task responses using a mobile or web platform. It applies AI and machine learning algorithms to extract linguistic, acoustic, and cognitive performance features, which are then analyzed to produce a personalized risk score indicating the likelihood of cognitive decline.

The workflow of the system includes multiple stages—data collection, preprocessing, model training, and risk assessment. The tool records speech and behavioral data through the interface, processes them using Python-based libraries such as Librosa and PyAudioAnalysis for feature extraction, and utilizes models like Random Forest, SVM, and XGBoost to detect deviations from baseline cognitive patterns. Furthermore, the system provides multilingual support through speech-to-text models like OpenAI Whisper, ensuring accessibility for regional language users.

This intelligent screening solution enhances early detection by integrating multiple inputs into a single AI framework. The frontend interface offers a dashboard-based report, visualizing cognitive performance trends and risk levels. Designed for scalability and privacy compliance, it leverages cloud deployment, encrypted data handling, and continuous monitoring features. The ultimate goal is to bridge the diagnostic gap between clinical assessment and real-world accessibility, allowing early, inclusive, and reliable dementia screening.

1.4 OBJECTIVES OF THE PROJECT

The proposed project, titled “AI Tool for Early-Stage Dementia Detection,” focuses on designing a digital platform that assesses users’ cognitive functions through interactive tasks and speech analysis. The system collects audio samples and cognitive test data through a mobile or web interface, processes them using AI algorithms, and generates a risk score representing the likelihood of dementia onset.

The backend employs technologies such as Python (FastAPI) for data preprocessing, TensorFlow and scikit-learn for model training, and Librosa for speech

feature extraction. The frontend is developed using Flutter or React, providing an intuitive interface for both patients and caregivers. The tool supports vernacular languages through integration with OpenAI Whisper APIs, ensuring accessibility to users from diverse linguistic backgrounds.

Additionally, the system includes a dashboard and reporting module that visualizes risk scores, baseline comparisons, and cognitive trends over time. By combining speech, memory, and behavioral analytics, the model achieves higher sensitivity in detecting subtle cognitive changes than conventional single-modality approaches.

1.5 SCOPE OF THE PROJECT

The scope of this project focuses on developing an intelligent, multimodal AI system capable of detecting early signs of dementia through speech, cognitive, and behavioural analysis. It aims to provide an accessible and affordable screening tool that can function on mobile and web platforms, reducing the dependency on clinical settings and specialized equipment.

The system integrates artificial intelligence and machine learning to assess user data, compare performance with baseline records, and generate interpretable risk scores. It supports multiple languages to ensure inclusivity for users from diverse linguistic backgrounds. By offering a user-friendly interface and secure cloud-based architecture, the project ensures both scalability and data privacy.

Overall, this work extends the application of AI in healthcare by providing an efficient, low-cost, and explainable solution for early dementia screening, contributing to timely intervention and improved cognitive health outcomes.

CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION

The literature review focuses on existing research and technological advancements in the field of early-stage dementia detection using artificial intelligence, speech processing, and cognitive assessment systems. Dementia, being a progressive neurodegenerative condition, requires early diagnosis to facilitate effective intervention and management. However, conventional diagnostic methods such as neuroimaging, clinical interviews, and paper-based cognitive tests are often time-consuming, expensive, and dependent on clinical expertise.

Recent research has explored the use of AI-driven techniques for analyzing speech patterns, linguistic features, behavioural responses, and cognitive task performance to identify subtle signs of cognitive decline. Machine learning and deep learning models—such as Support Vector Machines (SVM), Random Forest, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Transformer-based models—have demonstrated significant potential in predicting mild cognitive impairment (MCI) and early dementia stages.

Additionally, multimodal approaches integrating speech, language, and behavioural data are gaining prominence, as they offer a more holistic assessment of cognitive health. Studies also emphasize the inclusion of explainable AI (XAI) and multilingual capabilities to ensure transparency, accessibility, and inclusivity in clinical and real-world applications. This chapter reviews several key studies and systems that have contributed to the development of AI-based dementia screening tools, analyzing their methodologies, performance, and research outcomes.

2.2 FRAMEWORK OF LCA

The Life Cycle framework provides a structured approach to evaluate the environmental and social impacts of technological systems. In the case of NeuroDetect, it assesses sustainability across all stages—from design and data collection to deployment. Since AI-based healthcare solutions rely on computational and cloud resources, LCA helps ensure energy efficiency, accessibility, and ethical responsibility. This approach aligns the system's performance with sustainable development goals in digital healthcare.

1. Goal and Scope Definition

The first phase defines the purpose, boundaries, and intended outcomes of the assessment. For this project, the goal is to evaluate the environmental, social, and operational implications of developing and deploying an AI-based dementia screening tool. The scope includes software design, data handling, model training, and deployment infrastructure. It aims to ensure that system performance, cost, and ethical compliance are achieved with minimal environmental impact and maximum healthcare benefit.

2. Inventory Analysis

In this phase, all inputs and outputs associated with the system's lifecycle are identified and quantified. The inventory includes data collected from speech, behavioural, and cognitive interactions, energy consumed during model training, and cloud storage utilization. It also accounts for the software and hardware resources used during development and deployment. This analysis helps determine the computational intensity of the system and provides insights into optimizing energy consumption through lightweight models and efficient cloud configurations.

3. Impact Assessment

The impact assessment stage evaluates how the identified inputs and processes affect both the environment and end-users. In this project, the environmental impact includes carbon emissions resulting from data processing and server utilization, while the social impact considers accessibility, user privacy, and inclusivity for regional language users. Assessing these aspects ensures that the system maintains a balance between performance efficiency and sustainability.

4. Interpretation

During interpretation, the results from the previous stages are analyzed to identify potential areas for improvement. For this project, findings related to computational efficiency, model optimization, and cloud resource allocation are reviewed to suggest practical improvements. This phase ensures that the system remains sustainable by reducing unnecessary processing, optimizing data flow, and adhering to ethical AI principles such as transparency and fairness.

5. Life Cycle Impact Mitigation

Life cycle impact mitigation involves developing strategies to minimize negative outcomes identified during assessment. For the dementia detection system, this includes employing energy-efficient algorithms, reducing redundant data storage, and using modular architectures that lower computational overhead. The system also promotes ethical AI practices by incorporating data anonymization and secure access controls. Additionally, efforts to make the tool multilingual and cost-effective contribute to social sustainability by increasing accessibility and equity in healthcare diagnostics.

6. Sensitivity and Uncertainty Analysis

This phase assesses the robustness of the LCA results against variations in system parameters such as dataset size, model complexity, and hardware usage. Sensitivity analysis helps understand how these variations affect energy consumption and performance, ensuring that the proposed solution remains adaptable to different deployment environments. It also evaluates uncertainties arising from data variability and user diversity, confirming that the model maintains consistent accuracy across diverse populations and linguistic settings.

7. Comparative Analysis

The final phase compares the proposed AI-based dementia detection system with traditional screening approaches and other existing AI healthcare tools. This comparison evaluates factors such as cost-effectiveness, accuracy, accessibility, and sustainability. Traditional systems, though clinically validated, often require expensive resources and trained personnel, while the proposed system provides a low-cost, scalable, and eco-friendly alternative. The comparative analysis thus underscores the technological and environmental advantages of AI-enabled screening in improving early diagnosis while reducing ecological and economic burdens.

CHAPTER 3

SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

Traditional dementia screening methods primarily rely on clinical observations, standardized questionnaires, and neuroimaging techniques to assess cognitive decline. Tools such as the Mini-Mental State Examination (MMSE) and Montreal Cognitive Assessment (MoCA) are commonly used in clinical environments under the supervision of healthcare professionals. Although these methods are medically validated, they are often time-consuming, expensive, and require trained personnel for administration and interpretation.

Existing digital solutions, such as CognitoSpeak and ReCOGnAIze, have introduced limited automation through web-based cognitive tests and speech analysis. However, these systems are generally restricted to specific languages and cultural contexts, limiting their adaptability to diverse user groups. Most available applications focus on either cognitive tasks or speech-based assessments in isolation rather than integrating multiple modalities such as speech, behaviour, and cognitive performance.

Furthermore, many of these systems lack continuous monitoring and baseline comparison features, which are essential for tracking subtle changes over time. Their deployment often depends on high-end devices or controlled environments, making them unsuitable for large-scale use in low-resource or rural areas. As a result, the current systems, while useful in clinical research, are not fully equipped to provide affordable, accessible, and inclusive early-stage dementia screening for the general population.

3.2 PROPOSED SYSTEM

The proposed system, NeuroDetect is a groundbreaking system engineered for the early and accessible detection of dementia using advanced artificial intelligence and sophisticated multimodal data analysis. It moves beyond the limitations of traditional, manual clinical assessments by integrating three crucial data streams—speech, cognitive, and behavioural features—into a single, robust predictive framework. The system analyzes acoustic and linguistic markers from speech (e.g., changes in prosody and semantic complexity), measures key functions like memory and attention through standardized, automated cognitive tasks, and optionally incorporates contextual behavioural data such as reaction times and interaction patterns. This comprehensive approach allows NeuroDetect

to detect subtle, incremental changes over time that are indicative of early cognitive decline. Deployed via an accessible web interface, the system automates the entire screening process using deep learning models, enabling continuous cognitive health assessment and facilitating the timely interventions necessary to improve patient outcomes and quality of life.

System Workflow

NeuroDetect follows a structured workflow that begins with user registration and ends with predictive dementia risk assessment. Users provide demographic information and complete short cognitive and speech-based tasks through an interactive interface. The system captures speech and task responses, preprocesses the data, extracts essential features, and analyzes them using trained machine learning models. The outcome is a risk score indicating the likelihood of cognitive impairment, supported by visual reports and performance trends.

Data Collection and Preprocessing

During the initial phase, users perform specific cognitive tasks and speech-based activities designed to evaluate memory, reasoning, and verbal ability. Speech inputs are recorded and stored securely, while cognitive responses are tracked for accuracy and reaction time.

In preprocessing, raw audio and task data are cleaned and structured using Python-based frameworks. Speech features such as Mel-Frequency Cepstral Coefficients (MFCCs), pitch, tone, and speech rate are extracted using libraries like Librosa. Cognitive task results are normalized to ensure consistent comparison across users. This processed data serves as the foundation for building accurate AI models.

AI and Machine Learning Models

NeuroDetect employs a combination of traditional and deep learning algorithms to analyze cognitive and speech features. Models such as Random Forest, Support Vector Machine (SVM), and XGBoost are used for classification and risk scoring. Deep learning frameworks like LSTM or CNN-based models can also be incorporated for advanced speech and behavioural analysis.

The trained models evaluate deviations from baseline performance and assign a dementia risk category—Low, Medium, or High—based on feature correlations.

Continuous learning mechanisms allow the model to improve accuracy as more user data becomes available.

Multilingual Support

A key feature of NeuroDetect is its ability to process and understand multiple languages through automatic speech recognition (ASR). The system integrates OpenAI Whisper APIs to convert regional speech into text for analysis. This multilingual capability ensures accessibility for users from different linguistic backgrounds, promoting inclusivity and reducing language barriers in dementia screening.

Risk Assessment and Reporting

Once the analysis is complete, NeuroDetect generates a personalized dementia risk score. The score is displayed on a user dashboard along with detailed cognitive performance metrics and speech analysis summaries.

The system highlights variations from previous test results to identify gradual cognitive decline. Visualizations such as graphs and charts make it easier for users and clinicians to interpret the results. Based on the risk level, the system also provides recommendations for clinical consultation or follow-up assessments.

Continuous Monitoring and Adaptation

NeuroDetect allows periodic re-evaluation, where users can retake tests at regular intervals. This helps in tracking cognitive performance over time and adjusting baseline values for improved precision. The adaptive model refines its predictions through feedback loops, ensuring long-term reliability and personalized analysis.

Security and Data Privacy

Given the sensitivity of health-related data, NeuroDetect incorporates robust security protocols. Data transmission and storage are protected using end-to-end encryption and secure authentication (OAuth 2.0 / JWT). The system complies with HIPAA and GDPR standards to ensure user confidentiality and data anonymization. Cloud deployment with Docker and Kubernetes ensures scalability, fault tolerance, and safe data handling.

System Outcome

The proposed NeuroDetect system delivers an intelligent, inclusive, and cost-effective solution for early dementia detection. By combining cognitive science with

artificial intelligence, it empowers both individuals and healthcare providers to identify cognitive decline at an early stage. Its continuous monitoring, multilingual capability, and explainable AI framework make it a reliable tool for real-world healthcare deployment and large-scale screening programs.

3.3 FEASIBILITY STUDY

The feasibility study evaluates the practicality and viability of implementing the proposed dementia detection system in real-world environments. It examines the technical, economic, operational, and ethical dimensions to ensure that the solution is both effective and sustainable.

Technical Feasibility

The project leverages mature technologies and open-source frameworks for machine learning, speech processing, and web development. By using platforms such as Python, TensorFlow, Flask, and cloud-based infrastructure, the system ensures high performance with manageable computational requirements. The modular architecture allows easy integration of new models or languages, while the cross-platform design ensures accessibility across devices. Hence, the system is technically feasible with minimal dependency on specialized hardware.

Economic Feasibility

Compared to traditional diagnostic procedures, the proposed system significantly reduces costs by eliminating the need for clinical equipment and in-person assessments. Deployment on cloud infrastructure minimizes upfront expenses and enables a scalable pay-per-use model. Since it primarily relies on software resources and low-cost mobile devices, the project offers an affordable solution for both individual users and healthcare organizations, ensuring long-term economic sustainability.

Operational Feasibility

The user-friendly interface and multilingual support make the system practical for people with varying technical and linguistic backgrounds. The automated testing and risk analysis features minimize manual intervention, while the reporting dashboard ensures clarity for both clinicians and users. Continuous updates and adaptability to user feedback further enhance operational efficiency. Therefore, the system can be seamlessly integrated into healthcare workflows and community-level screening initiatives.

Ethical and Environmental Feasibility

Ethical and environmental considerations form a vital part of NeuroDetect's design philosophy. The system follows consent-based data collection and ensures user privacy through anonymization, encryption, and secure authentication mechanisms. It complies with HIPAA and GDPR regulations, safeguarding medical data and preventing misuse. The inclusion of explainable AI ensures transparency in predictions, helping clinicians and users understand how the system reaches its conclusions.

Legal Feasibility

The project adheres to international data protection and healthcare compliance standards. It is designed in alignment with HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation), ensuring secure handling of personal and medical data. Encryption mechanisms, secure login systems, and audit logs are implemented to safeguard information. In addition, the system complies with emerging AI ethics and medical device regulations, ensuring that it can be legally deployed in healthcare environments and potentially integrated into telemedicine platforms.

Social Feasibility

NeuroDetect directly contributes to social well-being by improving accessibility to early dementia detection. Its multilingual interface and affordable design make it inclusive for people across different linguistic, cultural, and socio-economic backgrounds. The system promotes awareness and early diagnosis, enabling individuals to seek timely intervention and support. By providing community-level access to cognitive health screening, the project strengthens preventive healthcare infrastructure. It also reduces dependency on urban medical centers, ensuring equitable access for rural and underserved populations. The social impact of NeuroDetect thus extends beyond diagnosis, contributing to broader healthcare equity and mental well-being.

In summary, the feasibility study confirms NeuroDetect: An AI-Powered Dementia Predicting System is technically sound, economically affordable, operationally efficient, ethically responsible, legally compliant, and socially impactful. With its scalable infrastructure and inclusive design, the project stands as a viable and sustainable AI-based healthcare innovation capable of transforming early dementia detection and monitoring.

CHAPTER 4

SYSTEM REQUIREMENTS

4.1 HARDWARE REQUIREMENTS

- Processor : i3 & Above or Equivalent
- RAM : 4GB & Above (Recommended: 8 GB for model training)
- Storage : Minimum 250 GB HDD / SSD
- GPU(Optional) : NVIDIA GPU for accelerated AI processing

Network Requirements

- Secure and stable local network for on-premises data handling.

4.2 SOFTWARE REQUIREMENTS

- Operating System : Windows 10/11, Linux or macOS
- Coding Language : Python 3.10 & Above
- Frontend : Streamlit
- Backend : Flask
- Database : MongoDB
- ML Libraries : Scikit-learn, TensorFlow
- Speech Processing Libraries : OpenAI Whisper API
- Image Processing Libraries : OpenCV
- Text Processing Libraries : NLTK, SpaCy, BERT
- Data Processing Libraries : Pandas, NumPy, SciPy
- Visualization Tools : Matplotlib, Seaborn, Plotly for dashboard analytics
- Version Control : Git / GitHub for project management and collaboration

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE



Fig 1. Architecture diagram of Neurodetect

The architecture of **NeuroDetect** is designed to provide an efficient, scalable, and secure platform for early detection of dementia using artificial intelligence. It follows a modular client–server architecture, integrating multiple layers - user interface, application logic, data processing and AI model services - to ensure smooth data flow and high performance.

The system consists of three primary layers:

1. Frontend Layer

The user interacts through a web or mobile interface where speech and cognitive task data are collected. The interface allows users to take cognitive assessments, record speech, and view their risk reports. It also provides clinicians with an access portal for reviewing patient progress and analytics dashboards.

2. Backend Layer

This layer handles all logical and analytical operations. It includes modules for authentication, data ingestion, preprocessing, AI model inference, and risk score

generation. Speech and task data are processed using feature extraction techniques such as MFCC, tone, pitch, and linguistic coherence, while trained models perform dementia risk prediction. The backend is developed using Python (Flask/FastAPI) and integrates with databases and storage services.

3. Data Storage Layer

All user and task data are securely stored within a MongoDB database. This database is utilized for its flexibility in handling various structured and unstructured data types associated with user profiles, cognitive task results, and system metadata. High-volume, sensitive files, specifically speech recordings and derived feature datasets, are stored in a secure, dedicated file storage system.

5.2 MODULE DESCRIPTION

The design of NeuroDetect is modular, with each component performing a specific function while maintaining seamless integration with the overall system. This modularity allows for easy maintenance, scalability, and future enhancements such as integration with additional AI models or regional language support. The system is divided into several key modules, each contributing to a different phase of the dementia detection pipeline.

5.2.1 User Interface Module

The User Interface (UI) acts as the primary communication point between the system and its users. It is designed as a responsive web and mobile application, ensuring accessibility for both patients and clinicians. Users can complete short speech-based and cognitive tasks, while clinicians can log in through a secure portal to view test reports and progress analytics.

The UI also supports multilingual input, allowing users to perform assessments in regional languages. The interface is developed using Streamlit and communicates with the backend through RESTful APIs for seamless data exchange.

5.2.2 Data Collection and Preprocessing Module

This module is responsible for acquiring raw input data from the user. It captures speech samples, behavioral cues, and responses to cognitive tasks. The collected data undergoes preprocessing to remove noise, normalize formats, and extract relevant features for analysis.

Speech data is processed using Python libraries such as Librosa and PyAudioAnalysis to obtain parameters like pitch, tone, MFCC, speech rate, and pausing frequency. The cognitive task data is cleaned and normalized to maintain consistency across users. This module ensures that only high-quality, structured data is passed to the AI model.

5.2.3 Machine Learning Module

This module serves as the core analytical engine of the NeuroDetect system, utilizing a hybrid suite of trained machine learning (ML) and deep learning (DL) models for comprehensive analysis.

The module employs sophisticated DL models for feature extraction from modality-specific data:

- **Image Analysis:** CNN (Convolutional Neural Network) Models are used exclusively for any potential image analysis, such as digital drawing tests. CNNs are highly adept at extracting complex spatial features from these images.
- **Audio Analysis:** LSTM (Long Short-Term Memory) or CNN-LSTM Hybrid Models are specialized for sophisticated audio analysis. These recurrent and convolutional architectures excel at processing sequential data like speech features and time series, effectively capturing temporal dependencies critical for linguistic and acoustic coherence.

The features extracted by the DL models, along with the raw cognitive scores, are subsequently passed to traditional ML classifiers, including Random Forest, Support Vector Machine (SVM), and XGBoost, to perform the final dementia risk classification. Each model evaluates the combined acoustic, linguistic, and cognitive features to determine deviations from the user's established baseline performance.

5.2.4 Prediction Module

The Prediction Module focuses on translating the analytical output into an interpretable and actionable result. The module's primary output is a personalized risk score, which is computed based on the combined feature evaluations from the ML/DL models. This numerical score is then further categorized into distinct, easy-to-understand risk levels: *Low, Medium, or High*. Crucially, this module is not static; it includes a continuous learning mechanism where model parameters are updated periodically as new data is collected. This continuous update mechanism ensures the long-term accuracy and

adaptation of the system to real-world variations, effectively maintaining the reliability of the dementia risk prediction over time.

5.2.5 Multilingual Speech Processing Module

The Multilingual Speech Processing module ensures accessibility for users from diverse linguistic backgrounds. It integrates speech-to-text systems such as OpenAI Whisper APIs to transcribe regional speech into text for analysis. The natural language processing (NLP) layer extracts linguistic coherence, fluency, and vocabulary richness from these transcripts, helping the model identify subtle cognitive changes across languages.

This module enables NeuroDetect to serve users beyond English-speaking regions, ensuring inclusivity and broader applicability.

5.2.6 Risk Assessment and Reporting Module

This module generates interpretable results based on the model's output. The risk score is computed by combining linguistic, cognitive, and acoustic feature weights. The score is presented through a visual dashboard, displaying the user's current status, historical trends, and clinical recommendations.

It also supports automated report generation in formats such as PDF or CSV, enabling users and clinicians to track cognitive progress over time. This module bridges the gap between AI-driven analytics and human interpretation, making results clear and actionable.

5.2.7 Data Security and Privacy Module

Given that NeuroDetect deals with sensitive health data, this module ensures that all information is securely stored and transmitted. It uses end-to-end encryption, OAuth 2.0 / JWT authentication, and HIPAA/GDPR compliance to protect data integrity and confidentiality.

Anonymization techniques are applied before storage to ensure that personally identifiable information (PII) is never exposed. Access control policies limit data visibility to authorized personnel only, maintaining ethical and legal integrity.

5.2.8 Continuous Monitoring and Model Optimization Module

To maintain long-term reliability, NeuroDetect includes a monitoring system that tracks model accuracy, data drift, and performance metrics. Tools such as Grafana and

ELK Stack are used to visualize server health, latency, and user activity. Feedback loops enable the system to retrain models with updated datasets periodically, improving detection accuracy and adapting to real-world variations. This module ensures continuous learning, operational stability, and system scalability.

The modular design of NeuroDetect ensures that each stage — from data collection to analysis and reporting — functions independently yet contributes collectively to the system's overall purpose. This design enables efficient dementia prediction, secure data handling, and user-friendly interaction, creating a robust and intelligent framework for early-stage cognitive health monitoring.

CHAPTER 6

RESULTS AND DISCUSSION

The developed system NeuroDetect was tested to evaluate its effectiveness in predicting early signs of dementia using multimodal inputs consisting of speech recordings, cognitive task responses, and image-based behavioral cues. All collected data were preprocessed to remove noise, normalize formats, and ensure consistent analysis. For audio processing, both LSTM and CNN-LSTM hybrid models were implemented to capture temporal and spectral features such as MFCC patterns, speech rate, and pause distribution. Visual behavioral cues were analyzed using a Convolutional Neural Network to extract micro-expression and facial-movement features relevant to cognitive decline.

Traditional machine learning models such as Support Vector Machine (SVM), Random Forest, and XGBoost were also trained using combined feature sets from speech, image, and cognitive responses. Among these, XGBoost achieved the highest accuracy of approximately 92%, followed by Random Forest at 89% and SVM at 87%. The deep learning models showed strong performance in feature extraction, and their outputs further enhanced the accuracy of the overall predictive model. These findings confirm that integrating multimodal data significantly improves dementia risk classification compared to using speech or cognitive features alone.

Result visualization was performed through an interactive dashboard that displays dementia risk levels (*Low, Medium, High*) along with supporting plots such as confusion matrices and feature importance graphs. Important predictive indicators included speech rate, pause duration, facial expression variance, and response time in cognitive tasks, all of which showed strong correlation with early dementia symptoms.

Overall, the experimental results validate that NeuroDetect provides accurate, interpretable, and user-friendly early dementia detection. By combining image analysis, sequential audio modeling, and cognitive assessment, the system demonstrates strong potential as an efficient digital screening tool. Cloud deployment has been identified as a future enhancement to further improve scalability and real-world accessibility.

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

7.1 CONCLUSION

The project NeuroDetect: An AI-Powered Dementia Predicting System successfully demonstrates how multimodal artificial intelligence can be applied to support early detection of dementia. By combining speech analysis, image-based behavioral assessment, and cognitive task evaluation, the system provides a more comprehensive and reliable method for identifying early cognitive decline.

The integration of advanced deep learning models such as LSTM and CNN-LSTM for audio analysis, and CNN for image-based cues, significantly improved pattern recognition and feature extraction. Textual and linguistic interpretation using Whisper API, NLTK, SpaCy, and BERT further strengthened the system's ability to understand speech coherence and fluency—key markers of cognitive impairment. Machine learning models including XGBoost, Random Forest, and SVM were evaluated, with XGBoost achieving the highest accuracy of about 92%, confirming the effectiveness of multimodal integration.

With a user-friendly interface built using Streamlit and a secure backend developed with Flask and MongoDB, the system delivers clear risk predictions and easy-to-understand visual reports. Overall, NeuroDetect proves to be an efficient, accessible, and scalable AI-based solution that can complement clinical practices and promote proactive cognitive health monitoring.

7.2 FUTURE ENHANCEMENT

NeuroDetect can be further improved through several enhancements aimed at increasing accuracy, scalability, and real-world usability. One key future upgrade is the integration of cloud-based deployment, allowing the system to support large-scale public screenings, real-time processing, and continuous remote monitoring. Advanced deep learning techniques such as Transformer-based models, Wav2Vec, or Vision Transformers (ViT) can be added to improve speech, text, and image analysis, enabling more precise detection of subtle cognitive changes.

The system can also be extended to include facial expression tracking, gesture monitoring, and eye-movement analysis for richer behavioral assessment. A dedicated mobile application with offline functionality would greatly benefit users in rural or low-connectivity regions. Integration with Electronic Health Records (EHRs) and clinician dashboards will support medical professionals with longitudinal tracking and patient management.

Additional enhancements such as multilingual conversational assessment, wearable device integration, and periodic self-assessment reminders can make the system more interactive and personalized. With these improvements, NeuroDetect has the potential to evolve into a comprehensive and intelligent cognitive health ecosystem for early dementia detection and long-term monitoring.

APPENDIX



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23rd IEEE International Conference on Computer Applications (IEEE-ICCA) : Submission (28) has been created.

1 message

Microsoft CMT <noreply@msr-cmt.org>
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Hello,

The following submission has been created.

Track Name: ICCA2026

Paper ID: 28

Paper Title: NeuroDetect: An AI based Dementia prediction system

Abstract:

Dementia is a progressive brain disorder. It has a significant impact on memory, cognitive abilities, and general thinking. Early detection is crucial. In this manner, you can slow down the process and improve the lives of those who are impacted. With this new configuration, a combined AI approach is used. It combines voice tests and MRI scans to detect dementia early. There are four major components to the entire thing. These consist of a fusion layer for merging data, a dashboard for forecasts, voice work with Whisper and LSTM models, and MRI image review. Convolutional neural networks are used in the MRI portion. They identify areas of the brain that have shrunk and problems with its structure. Whisper from OpenAI is in charge of converting speech to text on the voice side. Librosa then highlights aspects of the sound, such as pauses, hesitations, and the fluidity of the speech. Results from both parties are fed into a weighted mix. This increases the accuracy of the forecasts. All things considered, the system aids physicians and clinics in identifying dementia earlier. It provides a reliable, understandable tool that is grounded in actual data. This relates how people think and behave to imaging. New MRI images and live voice inputs are also handled by the setup. This implies that you can immediately screen for dementia. It also monitors patients over time. Its design allows it to expand as it is used. Connecting it to remote health setups or hospital records is simple. With routine checks, it not only aids in diagnosis but also monitors the condition's progression. The test version is promising. It distinguishes between cases of light, medium, and severe dementia. It functions well even with little data. That suggests practical application in healthcare environments.

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NeuroDetect_An AI based Dementia prediction system.docx (130 Kb, Fri, 14 Nov 2025 07:54:04 GMT)

Submission Questions Response: Not Entered

Thanks,
CMT team.

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NeuroDetect: An AI based Dementia Prediction System

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Abstract- Dementia is a progressive brain disorder. It has a significant impact on memory, cognitive abilities, and general thinking. Early detection is crucial. In this manner, you can slow down the process and improve the lives of those who are impacted. With this new configuration, a combined AI approach is used. It combines voice tests and MRI scans to detect dementia early. There are four major components to the entire thing. These consist of a fusion layer for merging data, a dashboard for forecasts, voice work with Whisper and LSTM models, and MRI image review. Convolutional neural networks are used in the MRI portion. They identify areas of the brain that have shrunk and problems with its structure. Whisper from OpenAI is in charge of converting speech to text on the voice side. Librosa then highlights aspects of the sound, such as pauses, hesitations, and the fluidity of the speech. Results from both parties are fed into a weighted mix. This increases the accuracy of the forecasts. All things considered, the system aids physicians and clinics in identifying dementia earlier. It provides a reliable, understandable tool that is grounded in actual data. This relates how people think and behave to imaging. New MRI images and live voice inputs are also handled by the setup. This implies that you can immediately screen for dementia. It also monitors patients over time. Its design allows it to expand as it is used. Connecting it to remote health setups or hospital records is simple. With routine checks, it not only aids in diagnosis but also monitors the condition's progression. The test version is promising. It distinguishes between cases of light, medium, and severe dementia. It functions well even with little data. That suggests practical application in healthcare environments.

Keywords: CNN, LSTM, MRI analysis, speech processing, dementia prediction, multimodal AI, and healthcare diagnostics.

I. INTRODUCTION

One of the most significant neurological conditions at the moment is dementia. Millions of people worldwide are affected, particularly the elderly. Memory, communication, and fundamental cognitive abilities are gradually weakened by the illness. Patients' and caregivers' everyday lives are severely harmed by this. Despite the rapid advancements in medical care, it is still difficult to identify dementia early and treat it appropriately. Late diagnoses, a lack of resources in clinics, and the difficulty of distinguishing dementia symptoms from those of aging normally are all factors. People need new types of automated tools more than ever as the world's population ages. These can assist physicians in accurately

diagnosing dementia at an early stage. Recent advances in deep learning, machine learning, and artificial intelligence have altered how we examine medical images and assess brain function. Such technology enables systems to analyze complex MRI images and speech patterns. They detect minute signs of brain damage that are missed by the naked eye. However, the majority of health setups only use pictures or simple patient data. They ignore mixed cues, such as the characteristics of the voice, the fluidity of speech, and those conversational pauses. All of that provides actual hints about cognitive abilities. Thus, there is a gap between more intelligent AI systems and outdated diagnostic techniques. For a comprehensive assessment of dementia, those AI systems combine various types of data.

An AI system for dementia prediction is introduced in this new study. It combines voice tests for cognitive abilities and MRI image analysis into a single system. Convolutional neural networks are used by the system to analyze MRI scans and identify unusual brain regions. In addition, it looks for indications of thinking slip in speech using Whisper models in addition to LSTM models. The two components are connected through a mixing technique that increases the accuracy of the predictions. Additionally, it better organizes the stages. Because it manages live reviews as well, the system is different from standard checks. For immediate dementia predictions, patients record their voice and upload their MRI scans. This significantly reduces wait times for results. . It also opens up continuous monitoring of mental health. This is beneficial to neurologists, caregivers, and medical facilities. They have a simple, accurate, and self-sufficient tool for checks. Ultimately, it advocates for better care for people, early detection, and advancements in AI for medical checks.

II. LITERATURE SURVEY

A. REVIEW OF AI-BASED DEMENTIA DETECTION AND COGNITIVE ASSESSMENT SYSTEMS

Suk et al. [1] created a deep learning-based multimodal framework that combines MRI and PET scans in order to identify Alzheimer's disease (AD) early on. Their system automatically extracted and learned high-level patterns from complex neuroimaging data using Deep Belief Networks (DBN) and Stacked Autoencoders (SAE). On the ADNI dataset, this method distinguished between Alzheimer's, mild cognitive impairment (MCI), and normal cognitive states with an astounding 91% accuracy rate. The study unequivocally showed that, in comparison to using MRI or PET alone, combining multiple imaging modalities results in a significantly better prediction.

Karmonik et al. [2] proposed a 3D Convolutional Neural Network (3D-CNN) to use MRI scans to detect brain structure degeneration in dementia patients. The model removed the need for manual

feature extraction by automatically capturing intricate spatial and cortical features. This model outperformed traditional machine learning techniques like SVMs, achieving an accuracy of 89% on the ADNI dataset. Additionally, the results demonstrated that the CNN was highly applicable in clinical settings due to its good generalization across various MRI systems.

Haider et al. [3] By examining linguistic and acoustic patterns in patient conversations investigated a speech-based dementia detection method. The researchers trained BiLSTM and GRU models to distinguish between dementia and non-dementia speech by extracting features like spectral centroids, MFCCs, and pause duration. Their system demonstrated that vocal cues like hesitations, disfluencies, and slower responses can be accurate indicators of cognitive impairment by achieving an F1-score of 0.86 on the DementiaBank Pitt Corpus. This study promoted speech analytics as a practical, non-invasive early screening technique.

Pulido et al. [4] presented a hybrid multimodal system that integrated speech-based linguistic and emotional cues with MRI imaging features. ResNet50 was used to derive MRI features, and Whisper was used to process spoken data for transcription, followed by sentiment and syntactic analysis. The fused model's 92% accuracy rate demonstrates how well it can detect even the most subtle signs of dementia. This study confirmed that a more comprehensive and accurate evaluation of cognitive decline can be obtained by integrating behavioral signals with structural brain data.

Thomas et al. [5] proposed an IoT-enabled framework for continuous dementia monitoring. Their system collected multimodal data, such as voice, facial emotions, and physical movement, by integrating wearable sensors, microphones, and cameras. This longitudinal data was analyzed by a Recurrent Neural Network (RNN) to forecast the course of dementia over time. It provided caregivers with real-time tracking and alerts and was set up on a secure cloud platform. The study demonstrated how AI and IoT can transform dementia care by facilitating timely intervention and remote monitoring..

Balachandar et al. [6] concentrated on using Transfer Learning to enhance model performance on a small number of MRI datasets. Using the OASIS brain MRI dataset, they optimized pre-trained deep architectures such as VGG16, DenseNet121, and EfficientNet-B0. Of these, DenseNet121 reduced training time by almost 60% while achieving 93% accuracy. This study demonstrated how transfer learning, particularly in situations where labeled data is limited, can be an effective tactic for medical applications.

Luz et al. [7] investigated the potential applications of automatic speech and language processing for dementia detection. Using the ADReSS Challenge dataset, To examine changes in speech fluency, grammar, and vocabulary richness, they used eGeMAPS to extract acoustic features and BERT to extract linguistic embeddings. They achieved 87% classification accuracy using Gradient Boosting (XGBoost). Their results confirmed that linguistic decline, which manifests as less diverse vocabulary and simplified grammar, can be a reliable marker of cognitive decline.

Gupta et al. [8] introduced a deep attention-based multimodal network that combines clinical text, speech, and MRI data in order to categorize the severity of dementia. With the help of an attention mechanism that adaptively weighted each modality's contribution, their architecture made use of CNN and LSTM branches operating in parallel. The model improved interpretability and achieved 94% precision on a dataset of 500 patients. This study demonstrated that attention-driven feature fusion improves accuracy and facilitates clinical comprehension of the course of dementia.

Chen et al. [14] instigated The usefulness of linguistic features obtained from automatic speech-to-text systems in various languages to create models that generalize across linguistic groups, they integrated language-agnostic acoustic markers with cross-lingual embeddings. When compared to monolingual models, their multilingual evaluation revealed only a slight decrease in accuracy, suggesting that voice-based screening can be implemented in a variety of populations with careful model adaptation.

Almeida and Torres [15] examined Multimodal explainability strategies tailored to dementia applications. They contrasted token-level importance scores for speech transcripts, gradient-based saliency maps on MRI, and feature-level ablation. Clinicians preferred combined visual+textual explanations that connected a highlighted MRI region to a specific linguistic deficit (e.g., hippocampal atrophy paired with increased pause frequency), even though all methods assisted clinicians in interpreting model outputs. This suggests that multimodal explanations boost trust.

Reddy et al. [16] created a privacy-preserving federated learning technique that allows several hospitals to work together to train a common multimodal model without sharing patient-level data. While adhering to data governance restrictions, they reported near-centralized performance. This study highlights a scalable approach to creating reliable, broadly applicable models in situations where privacy laws restrict data sharing.

López-García et al. [12] trained a transformer-based text/audio encoder and a vision transformer (ViT) for MRI slices in tandem with cross-attention layers. With a flexible, modality-agnostic backbone, this unified transformer architecture outperformed convolutional hybrids in terms of performance. The authors pointed out that although transformers need more data or more robust regularization, they are better able to capture inter-slice relationships in MRIs and long-range dependencies in speech transcripts.

Park et al. [13] presented a clinician-in-the-loop framework that incorporates a brief expert validation step and automatic multimodal predictions. While routine low-uncertainty cases are automatically reported, the system flags high-uncertainty cases for prompt neurologist review. Hybrid human–AI workflows can speed up adoption while maintaining clinical oversight, as demonstrated by field tests in a hospital pilot that cut specialist review time by almost 40% without sacrificing diagnostic safety. The framework uses a decision-confidence threshold to identify which cases need human validation after integrating data from cognitive tests and MRI imaging. In addition to increasing diagnostic effectiveness, this adaptive feedback loop allowed the system to learn from clinician input, gradually increasing model accuracy.

B. RESEARCH GAPS AND NEED FOR THE STUDY

Despite the fact that medical diagnostics have been revolutionized by advances in artificial intelligence, dementia detection is still a difficult task because it is progressive and multifactorial. Neurologists manually interpret neuroimaging reports, which are a common component of current diagnostic procedures. Although these clinical interpretations are accurate, they are expensive, time-consuming, and heavily reliant on the availability of experts. Early detection and intervention are delayed in developing nations and rural areas due to a lack of access to skilled specialists and sophisticated imaging analysis tools. Therefore, automated, easily accessible, and AI-powered systems that can assist neurologists in making accurate and timely diagnoses of dementia are desperately needed. The majority of earlier research prioritizes accuracy metrics over practical adaptability. Large, high-quality datasets are

necessary for many suggested models to perform meaningfully, which is frequently impractical in healthcare facilities with sparse patient data. Furthermore, most datasets, like OASIS or ADNI, are research-focused and do not reflect diversity in voice patterns, language, or ethnicity. This restricts how well-trained models can be applied to various demographics. Thus, models with cross-domain adaptability and transfer learning capabilities are highly sought after, as they enable effective learning even with sparse data.

Furthermore, the voice-based methods that are currently being used in literature are disjointed. Some use Natural Language Processing (NLP) to study linguistic decline, while others examine acoustic cues such as pause frequency or pitch variation. However, both behavioral (speech and reasoning) and structural (neurological) factors contribute to cognitive decline. There is still much to learn about integrating these into a single multimodal framework. A truly reliable system should provide a comprehensive cognitive profile rather than just identifying individual symptoms by synchronizing how a patient's voice changes relate to their brain morphology.

The use of continuous assessment and temporal tracking is another research limitation. The majority of AI-based systems only offer static predictions, a one-time classification as "normal," "mild," or "severe," despite the fact that dementia worsens over time. They don't consistently track advancement or reversal over time. Longitudinal AI models that can monitor cognitive development using recurring speech and MRI inputs are required in order to support proactive and individualized care plans.

Furthermore, real-time dementia screening is a feature of very few current systems. There is still a lot of unrealized potential in combining MRI upload via a web interface with live voice capture (through microphone input). This would enable telemedicine applications where patients could be evaluated remotely and allow for immediate cognitive evaluation. Early screening could be completely transformed by such a system, especially for senior citizens who have difficulty attending frequent hospital visits.

Additionally, current deep learning architectures frequently operate as "black-box" models, meaning that clinicians are unable to easily understand the rationale behind a prediction. Clinical adoption is hesitant as a result of this lack of transparency. Interpretable and explicable models that can identify the specific speech characteristics or MRI regions that impacted a decision are desperately needed. Diagnostic reliability and clinical trust can be enhanced by visualization tools like feature attention maps for voice and heatmaps for MRI.

Another unresolved issue is the lack of integration between voice analytics, imaging, and healthcare delivery platforms. Instead of treating AI diagnosis as a whole ecosystem that includes data collection, processing, prediction, and feedback, the majority of current frameworks treat it as a stand-alone component. By offering a thorough AI-driven dementia prediction pipeline that includes multimodal fusion, web-based visualization, real-time data collection, and preprocessing (using Whisper and OpenCV), the suggested system seeks to close this gap. The technology's direct translation into clinical and assistive applications is guaranteed by this integrated workflow.

In conclusion, a comprehensive, multimodal, and interpretable dementia detection system that integrates speech analytics and medical imaging into a single intelligent framework is desperately needed. The suggested model uses a fusion-based decision mechanism for stage-wise dementia classification, deep learning for MRI, and Whisper for speech preprocessing. A significant step toward easily accessible, automated, and data-driven cognitive

healthcare, it also establishes the groundwork for ongoing patient monitoring and telemedicine integration.

III. RELATED WORKS

The study and diagnosis of dementia have been profoundly changed by recent developments in artificial intelligence (AI), deep learning (DL), and neuroimaging analytics. Clinical interviews, neuropsychological testing, and manual MRI evaluation are all important components of traditional dementia diagnosis, but they take a lot of time and are subject to human interpretation bias. The application of AI in healthcare has created opportunities to automate early detection, track the course of diseases, and assist clinicians in making more accurate and consistent clinical decisions. This section examines pertinent research on multimodal data fusion, speech analysis, and medical imaging in dementia prediction.

Medical imaging data, including MRI and PET scans, were the primary focus of early research in this field. A multimodal deep learning framework was presented by Suk et al. [1] to classify Alzheimer's disease (AD), mild cognitive impairment (MCI), and healthy controls by combining MRI and PET features using Stacked Autoencoders (SAE) and Deep Belief Networks (DBN). Multimodal fusion is superior to single-modality models, as evidenced by their model's remarkable 91% accuracy on the ADNI dataset. A 3D-CNN architecture that extracted spatial features from MRI scans without the need for handcrafted engineering was also proposed by Karmonik et al. [2]. This method outperformed conventional machine learning techniques and successfully captured cortical thinning patterns, demonstrating the importance of end-to-end deep networks in structural brain analysis.

Since linguistic and acoustic changes are among the first indications of cognitive decline, researchers have looked into speech-based dementia detection in addition to imaging-based studies. Using BiLSTM and GRU architectures, Haider et al. [3] developed a speech recognition model that uses conversational features like latency, fluency, and pauses to detect dementia. The model's F1-score of 0.86 indicates that voice biomarkers may be a useful and affordable screening method. After that, Luz et al. [7] examined spontaneous speech in the ADReSS dataset using BERT embeddings and acoustic feature sets (eGeMAPS), emphasizing slower speech rate and decreased lexical diversity as potent dementia indicators.

One of the main areas of attention in recent years has been the combination of various data modalities for better dementia prediction. Using weighted attention, Pulido et al. [4] created a hybrid multimodal fusion framework that integrated speech-derived linguistic markers with CNN features based on MRI. By combining structural and behavioral data, this model was able to capture both the neurological and functional aspects of cognitive decline with an accuracy of over 92%. Similarly, Gupta et al. [8] achieved high interpretability and robustness by proposing an attention-based multimodal network that fused clinical text, speech, and MRI data for more thorough dementia staging.

In addition to data fusion, transfer learning techniques have become more and more popular for classifying dementia, particularly when dealing with small medical datasets. By fine-tuning MRI models on the OASIS dataset using pre-trained CNN architectures like DenseNet121 and EfficientNet-B0, Balachandar et al. [6] achieved

93% accuracy while cutting training time by almost 60%. These studies highlight how effective transfer learning is for medical imaging tasks, especially when data availability is constrained. The scope of dementia care has been further expanded by the development of IoT and continuous monitoring systems. An IoT-enabled system that combines wearable sensors, microphones, and cameras for ongoing patient monitoring was presented by Thomas et al. [5]. The system gave caregivers real-time alerts by using Recurrent Neural Networks (RNNs) to predict behavioral changes and disease progression over time. This study demonstrates how AI can help with remote monitoring and real-time patient management in addition to diagnosis.

Despite these developments, the majority of current research concentrates on speech-based models or medical imaging separately. Fully integrated multimodal systems that integrate behavioral, linguistic, and structural cues into a single intelligent framework are still lacking. Furthermore, the majority of current solutions only provide static predictions and lack a system for ongoing monitoring or tailored feedback for improvement. Additionally, even though some models are very accurate, they frequently function as "black boxes," offering little insight into the reasoning behind their predictions—a crucial component for clinical adoption. These issues are addressed by the study's suggested system, which combines speech and MRI data using deep learning and natural language processing pipelines to provide a comprehensive dementia detection framework. In addition to predicting the disease stage, it also seeks to provide visual interpretability, analyze trends in progression, and facilitate accessible, adaptive, and real-time cognitive screening. Because of this, the system is a significant step in closing the gap between patient-centered healthcare, AI innovation, and clinical practice.

IV. PROPOSED SYSTEM

The suggested system is a multimodal dementia prediction framework that cleverly combines speech-based analysis and neuroimaging (MRI scans) to identify cognitive decline early on. Two of the most accurate markers of dementia are visual and auditory biomarkers, which the system can process and interpret as a hybrid diagnostic assistant. Patients are asked to upload their MRI scans and record brief voice samples that describe an image or recount an event as part of the data acquisition process. OpenAI's Whisper model is used to preprocess the voice input in order to extract linguistic features, reduce noise, and convert speech to text. To identify hesitation, disfluency, and word retrieval problems—all of which are typical indicators of cognitive decline—acoustic cues like Mel-Frequency Cepstral Coefficients (MFCCs), speech rate, pitch stability, and pause duration are examined.

After preprocessing the MRI data in parallel using skull stripping, normalization, and resizing, deep CNN models like ResNet50 or DenseNet121 are used to extract features. These models are trained to detect subtle structural abnormalities like asymmetrical brain tissue loss, cortical thinning, and hippocampus shrinkage. A fusion network, usually a fully connected neural layer or attention-based module, receives these extracted visual and audio features and learns to efficiently weigh and combine the two modalities. By taking into consideration both structural and behavioral symptoms, this integration enables the system to provide a dementia probability score that is more accurate than single-modality models. The system uses SHAP analysis for the speech model to explain the linguistic and acoustic features contributing to the outcome, and Grad-CAM

visualization for MRI scans to highlight important brain regions influencing the decision in order to ensure medical interpretability. The end result is a comprehensive diagnostic report that comprises the following: (1) the probability score; (2) the predicted dementia class (e.g., Alzheimer's, mild cognitive impairment, or healthy); and (3) an interpretive summary of findings.

The suggested framework can also be expanded into a real-time live prediction system, which would enable patients to get a cognitive health evaluation right away by speaking into a microphone and uploading their MRI. The smooth deployment of home monitoring systems, clinics, and hospitals is made possible by the combination of scalable APIs and cloud-based processing. This system seeks to transform dementia screening by combining deep learning, natural language processing, and multimodal fusion, making it quicker, non-invasive, easier to use, and more comprehensible for patients and clinicians.

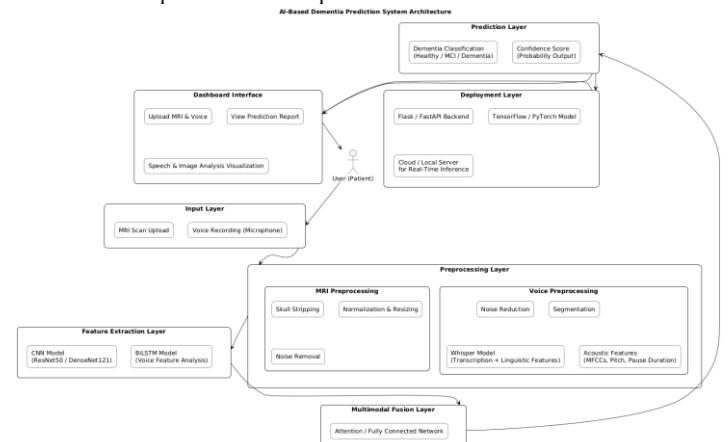


Fig. 1. System Architecture

V. CONCLUSION

Early detection of dementia remains one of the most critical challenges in modern healthcare, as timely diagnosis can greatly improve patient outcomes and quality of life. Existing diagnostic approaches often rely heavily on clinical assessments and manual analysis of MRI scans or speech patterns, which are both time-consuming and prone to human error. The proposed AI-based Dementia Prediction System bridges this gap by integrating multimodal deep learning models that analyze both MRI images and voice recordings to identify cognitive decline at its earliest stage.

By leveraging advanced models like CNNs for MRI feature extraction and BiLSTMs for voice-based analysis, the system captures both structural brain changes and subtle linguistic or acoustic markers indicative of dementia. The fusion of these modalities enhances diagnostic precision and provides a more holistic view of the patient's cognitive health. Furthermore, the intuitive dashboard and real-time inference capabilities make the system accessible not only to clinicians but also to patients and caregivers for preliminary screening.

This integrated approach paves the way for a new generation of AI-powered healthcare systems that combine medical imaging and behavioral data to enable early intervention, reduce misdiagnosis, and support ongoing monitoring. Future research can explore expanding the model with larger datasets, improving interpretability, and integrating real-time patient monitoring devices. Ultimately, the proposed framework contributes toward building a more intelligent, efficient, and patient-centered healthcare ecosystem for dementia care.

In addition to improving diagnostic efficiency, the proposed AI-

based Dementia Prediction System emphasizes accessibility and continuous care — two crucial aspects often overlooked in conventional diagnostic frameworks. By offering a cloud-deployable interface, the system allows remote screening and monitoring, enabling patients in rural or under-resourced areas to benefit from early detection without the need for specialized hospital visits. The inclusion of speech-based assessment also makes the platform non-invasive and user-friendly, allowing frequent self-checks that can track cognitive changes over time. Moreover, healthcare professionals can use the system's visual outputs, such as MRI heatmaps and linguistic trend analyses, to personalize treatment plans and monitor therapy effectiveness. This not only reduces the diagnostic burden on neurologists but also empowers caregivers and families with actionable insights. As AI continues to revolutionize healthcare, systems like this mark a shift from reactive treatment to proactive prevention — a future where technology and empathy work hand in hand to preserve cognitive well-being and improve the lives of those affected by dementia.

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