Innovations in Speech Recognition Technology for Improved Alzheimer's Care and AI Based Support Systems

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DECLARATION

I declare that this is my own work and this dissertation1 does not incorporate without acknowledgement any material previously submitted for a degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The supervisor/s should certify the proposal report with the following declaration.

The above candidate has carried out research for the bachelor's degree Dissertation under my supervision.

04/11/2025

……………………………… ………………………………

Mrs. Uthpala Samarakoon
Supervisor

Date

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Finally, I thank my friends and family for their continuous support and moral encouragement throughout the creation of this project.

Abstract

Alzheimer's disease is a progressive neurological condition that severely impacts memory, communication, and cognition. Its early and accurate determination of stages is important for its effective care planning, intervention, and management. This paper presents the design and development of a mobile app based on artificial intelligence (AI) for the identification of the clinical stage of Alzheimer's disease based on the Global Deterioration Scale (GDS) [1]. The proposed solution integrates two machine learning models: one for speech analysis and recognition and another for facial emotion detection [2].

The app features an interactive assessment interface where the patients respond to five clinically relevant questions via microphone and camera. Using speech-to-text, the speech module identifies key linguistic features like speech rate (WPM), pauses, fillers, and repetition patterns. Meanwhile, the vision module identifies emotional states like confusion or normal behavior via facial expression recognition. These multimodal inputs are analyzed, and the patients are classified into three broad cognitive stages: Pre-Dementia (GDS stages 1–3), Mild to Moderate Dementia (GDS stages 4–5), and Severe Dementia (GDS stages 6–7) [1].

The application provides real-time diagnostic feedback and additionally maintains a history log for tracking cognitive development over time. It empowers caregivers and clinicians by providing access to intuitive, AI-driven insights into the cognitive health of Alzheimer's patients. This solution bridges the gap between home-based monitoring and clinical diagnosis, particularly in low-resource settings. The research also includes a validation phase through accuracy testing, usability testing, and adherence to clinical standards. Overall, the project demonstrates the potential of AI-driven mobile health solutions in fostering early detection, continuous monitoring, and improved care for Alzheimer's disease patients.

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LIST OF ABBREVIATIONS

Abbreviation	**Description**
ML	Machine Learning
GDS	Global Deterioration Scale
WHO	World Health Organization
AD	Alzheimer's disease
NLP	Natural Language Processing
CNN	Convolutional Neural Network
WPM	Words Per Minute
AI	Artificial Intelligence
UI	User Interface
UX	User Experience

1. INTRODUCTION

1.1. Background & Literature Survey

Alzheimer's disease (AD) is a severe neurodegenerative disorder with overwhelming prevalence among the elderly that leads to immense cognitive, behavioral, and functional impairment. AD is the causative factor behind 60–80% of dementia cases across the world. The World Health Organization (WHO) estimates over 55 million people with dementia in the current world and suggests that this count will increase to 139 million by the year 2050 due to increasing numbers of the elderly population. Alzheimer's not only affects the person with the disease but also places emotional, financial, and physical burdens on caregivers and healthcare systems [2] [3].

Early diagnosis and proper staging of the disease are crucial for successful treatment planning and caregiving interventions. The Global Deterioration Scale (GDS), created by Dr. Barry Reisberg, Director of the Fisher Alzheimer's Disease Education and Research Program at NYU Grossman School of Medicine, is a formal clinical tool to measure the course of cognitive decline in Alzheimer's patients. Seven stages of the GDS are divided into pre-dementia (Stages 1–3) and dementia (Stages 4–7) stages. Stage 5 is generally the stage when the individual is no longer able to live alone. [1]

Each stage of Alzheimer's has particular cognitive and behavioral signs, including alteration in memory, language, orientation, problem-solving, and emotional stability. Change in speech and language patterns is one of the most significant observable signs that progress through the stages. In the early stages, patients can have mild word-finding difficulties and occasional hesitations. As the disease progresses, speech becomes less fluent, vocabulary declines, and individuals are repetitive or incomprehensible. In the end stages, speech is severely handicapped or even completely lost [4].

Recent advancements in mobile technologies and artificial intelligence (AI) [4] offer new opportunities to develop tools for early diagnosis and continuous monitoring of Alzheimer's disease. In particular, mobile health (mHealth) applications have emerged as promising platforms to provide low-cost, scalable, and non-invasive solutions to diagnose and monitor cognitive impairment. These platforms are likely to use in-built smartphone sensors such as microphones and cameras, and AI models to track the behavior of the user and make clinical inferences.

One of the most promising techniques in this area is machine learning (ML) analysis of facial expressions and speech. Speech has numerous biomarkers of cognitive state, including speech rate (words per minute), filler words (e.g., "uh," "um"), hesitation features, clarity of articulation, and sentence complexity. Typical adult speech is usually between 125–160 words per minute (wpm). In mildly to moderately demented Alzheimer's patients, this can drop to 100–120 wpm, while in severely demented Alzheimer's patients, it is possible to speak at a speed less than 90 wpm or remain non-verbal. Several studies have shown that disfluencies and increased pauses are predictors of mild cognitive impairment (MCI) and can predict incipient decline [4] [5].

At the same time, facial expression analysis proved to be useful in detecting states of mood such as confusion and normal. Real-time video analysis using deep learning methods can be applied to classify facial expressions and connect them to cognitive load and emotional distress, particularly during diagnostic interviews.

Numerous studies and projects have attempted to combine these modalities. For example, the "ADReSS Challenge" suggested a benchmark for speech-based Alzheimer's detection. Some research articles also investigated using natural language processing (NLP) [1] for Alzheimer's identification based on conversation analysis. However, most are confined to laboratory environments, with advanced equipment or clinical environments. Very few solutions offer real-time, mobile-based assessment using speech as well as facial expression analysis in combination with clinically validated staging systems like GDS.

1.2. Research Gap

Despite the developments in Alzheimer's diagnosis through AI and mobile health technologies, there are some gaps in the current space:

- **Lack of clinically aligned mobile apps:** Most current mHealth apps are designed for general brain training, medication reminders, or caregiver support. Few offer diagnostic capabilities, and even fewer are designed in line with medical standards like the Global Deterioration Scale. This limits their adoption and credibility in clinical environments.
- **Limited use of multimodal data:** The majority of existing applications rely solely on questionnaires or memory games. These approaches neglect the abundance of multimodal behavioral data, such as speech and facial expressions, that are reflective of cognitive well-being.
- **Limited personalization and interactivity:** Most of the apps have static interfaces and pre-decided questions without changing based on user behavior or mood. Interactive interview format — similar to the one used by doctors — however, can significantly increase the reliability of the tests.
- **Speech analysis without clinical benchmarks:** Some speech-based tools evaluate language fluency or sentiment, but they are not grounded in clinical speech rate norms or patterns within Alzheimer's patients. This makes it difficult to tie results back to actual disease progression [5] [7].
- **No incorporation of mood state:** Intellectual tasks in Alzheimer's patients are usually accompanied by emotional states such as frustration or confusion. Most tools ignore this factor, although mood can directly influence speech and decision-making ability [8] [9] [10].
- **No record keeping of user history and progress reports:** Long-term monitoring of disease progression is essential for personalized care. Many tools lack provisions for storing, plotting, and comparing test scores over time.

By bridging these gaps, it is possible to develop a new kind of mobile application—one that is accessible, clinically based, and backed by intelligent systems capable of analyzing data and making decisions in the moment.

Research papers analyzed

Research 1: Facial Expression Recognition to Support the Early Detection of Alzheimer's Disease: A Systematic Review [6].

Research 2: TDetect: A deep learning-based system for Alzheimer's detection through conversational speech analysis [4].

Research 3: A deep learning approach to on-node sensor data analytics for mobile or wearable devices [7].

Research Gap	Research1	Research2	Research3	Proposed System
Facial mood recognizes	YES	No	NO	Yes
uses machine learning (ML) to recognize various speech patterns with high accuracy.	NO	YES	NO	YES
mobile-based, AI-driven solution.	YES	NO	NO	YES
Detect GDS Alzheimer's level using APP conversation with voice	NO	NO	NO	YES
Use new Technologies (Flutter)	NO	NO	NO	YES
Designed for Non-Expert Users	NO	NO	NO	YES

Figure 1 Research Gap

1.3. Research Problem

This project aims to solve the following research problem:

"How can a mobile-based application utilize speech and facial mood analysis to detect and classify Alzheimer's disease stages according to the Global Deterioration Scale (GDS)?"

To respond to this, we propose a mobile application that possesses the following features:

- User Interface and Flow: Once the user opens the application and accesses the dashboard, they can simply press a button labeled "Cognitive Stage Identifier". It opens an interactive diagnostic session which is intended to mimic a doctor's interrogation.

- Structured Questioning: Five clinically relevant questions that are routinely used by specialists for initial cognitive assessment are generated by the application. These are:

  "Today's date is what?"
  "Name three usual objects?"
  "Who is the current president?"
  "Where are you at now?"
  "Can you count down from 20?"

- Real-Time Data Collection: During the session, the app allows the microphone and camera to capture verbal and non-verbal data. The speech is translated using a speech-to-text engine, and key features like speaking rate, filler words, and pauses are derived.

- Speech Analysis Model: The first ML model examines transcriptions and audio metadata to find indications of cognitive impairment. The model considers the following parameters:

  1. Word per minute (WPM)
  2. Number of filler words
  3. Type of filler words
  4. Total pause duration
  5. Sentence complexity and cohesion

- Mood Detection Model: The second ML model accepts camera input to analyze facial expressions in real-time and categorize the user's mood into categories like "normal", "confused", or "stressed". This imparts emotional significance to the responses provided and can also affect the stage classification.

Figure 2 Mood detection

- Stage Detection Engine: Based on extracted speech and mood features, the app categorizes the user into one of three diminished GDS levels:

Level 1 (GDS 1–3): Early Dementia
Level 2 (GDS 4–5): Moderate Dementia
Level 3 (GDS 6–7): Severe Dementia

- Final Report and History Log: When the session is complete, the app generates a brief report indicating the stage detected, speech measurements, mood measurements, and suggestions. A history page saves old sessions for observation of changes over time, facilitating caregivers as well as clinicians.

This project not only demonstrates the potential of AI-fueled mHealth apps but also sets an example of the way mobile technology can be aligned with clinical knowledge to deliver helpful diagnostic assistance for neurodegenerative conditions like Alzheimer's. The aim is to enable early detection, remove diagnostic delays, and give users continuous, real-time cognitive health tracking features. [1] [2] [3] [4]

1.4. Research Objectives

1.4.1. Main Objective

The primary objective of the current study is to design an application from a mobile phone that uses speech analysis and face mood recognition to detect and categorize the advancement of Alzheimer's disease in an individual based on the Global Deterioration Scale (GDS) [1]. The application, with the integration of artificial intelligence (AI) and machine learning (ML) techniques, will be an easy-to-use, non-invasive, and convenient system for early diagnosis and continuous evaluation of cognitive decline.

The system will help individuals, caregivers, and healthcare professionals using clinical observations of real-time face and speech patterns, thus creating early intervention as well as enhanced care strategies.

1.4.2. Specific Objectives

For achieving the overall goal, the following specific objectives have been set:

1. Development of Multimodal Diagnostic Interface

Implement and incorporate an user-friendly interface by which the users can initiate the Alzheimer's stage detection process with the use of a special code named "Cognitive Stage Identifier." The interface should be capable of welcoming the users, providing orderly questions, and recording audio and video inputs without any disturbance. It should mimic clinical settings to encourage the users and authenticate data collection [10].

2. Clinically Valid Questionnaire Integration

Integrate within the app a formal, five-question interview format with questions that are commonly used by doctors in cognitive examinations. The questions will evaluate the areas of memory recall, temporal orientation, naming, and simple reasoning. The questions must be clear, culturally neutral, and suitable for individuals with varying levels of cognitive status [8].

3. Speech Recognition and Analysis Implementation

Implement and include a speech-to-text converter to live transcribe the input from the user. The module has also to pick out linguistic features as well as acoustic features such as:

- Word per minute (WPM) rate
- Use of filler words ("uh," "um," etc.)
- Pause and hesitation
- Repetition and disfluencies
- Complexity in sentence structure

These are used to recognize markers of cognitive deterioration that identify signs of Alzheimer's disease stages [2] [1].

4. Mood Detection with Camera-Based Facial Analysis

Implement and deploy a facial recognition model using a camera to determine the emotional state of the user during the interview. The system needs to classify expressions into three groups:

- Normal
- Confused
- Distressed

The emotional feedback will be used to improve the stage classification accuracy and provide a better indication of the cognitive status of the user.

5. Categorization Based on Global Deterioration Scale

Map the information on speech and facial mood data to the seven clinical stages of the Global Deterioration Scale. For ease of reference and easy comprehension, categorize these into three broad levels:

Level 1 (Stages 1–3): Early Dementia

Level 2 (Stages 4–5): Moderate Dementia

Level 3 (Stages 6–7): Severe Dementia

The goal is to produce a classification that will be easily understandable by users and caregivers and yet still be clinically meaningful [1].

6. Generate and Display Assessment Reports

Implement a result generation module that provides users with a simple and understandable report of their cognitive status. The report should be able to capture the determined level of GDS, salient speech and mood features observed during the session, and any recommended follow-up action. This will ensure the user understands the message and can provide the results to a medical professional if necessary.

7. Implement History Tracking and User Data Logging

Add a history page to the application that logs all previous assessments. This feature will allow tracking of change over time, monitoring trends in mood or speech, and enabling ongoing medical monitoring or treatment. This makes the program not only an event-based application but also one that allows long-term cognitive health monitoring.

8. Make it Accessible and Usable

Make the system accessible and inclusive for older people and those with very basic technical knowledge. This entails simple navigation, clear audio and visual feedback, and support for multilingual interaction where necessary. The application must be equally compatible with many devices, ranging from low- to middle-grade smartphones.

2. METHODOLOGY

The methodology adopted in this project is a mix of software development and research-based methodology with a blend of clinical validation, building of machine learning models, and user-oriented mobile app design. The section is divided into several major components: requirement gathering and analysis, system design and architecture, model development (speech and mood analysis), implementation and integration, and testing and validation.

2.1. Requirement Gathering and Analysis

A thorough requirement analysis was conducted as the foundation to develop an AI-based mobile application for the detection of Alzheimer's stage. The phase utilizes the primary and secondary methods of data collection.

2.1.1. Primary Data Gathering and Analysis

Primary data were collected by:

- To further develop an understanding of the research topic and identify the current gaps, we personally met Mrs. Susan Fernando at the Lanka Alzheimer's Foundation in Maradana, Sri Lanka. The visit provided an opportunity for us to connect directly with a person who is closely involved with Alzheimer's patients and made us understand the applied importance and real-life application of our research.

- Clinical specialists, including neurologists and geriatric care professionals, were consulted.
- Alzheimer's Foundation Sri Lanka members were interviewed, which provided valuable background information on patient care and diagnostic problems within the local setting.

- Informal interviews were conducted with caregivers and family members of Alzheimer's patients.

Figure 3 Data gathering from Alzheimer's foundation

Some of the most significant findings from this phase are:

- Orientation and memory-related questions are typically posed by clinicians to ascertain cognitive status.
- Speech behavior (delayed rate, fillers, pauses) is a very early marker for Alzheimer's.
- Confusion or blank facial expressions typically follow cognitive effort.
- There is a strong need for a mobile, non-invasive screening tool, especially in rural or underserved areas.

This feedback directly influenced choosing features in the app: formal interrogation, mood rating, and voice analysis, with a history-tracking capability to track improvement.

2.1.2. Secondary Data Gathering and Analysis

Secondary data included:

- Reading scientific literature for the detection of Alzheimer's based on speech and facial cues.

- An examination of clinical tools like the Global Deterioration Scale (GDS).
- Evaluation of existing digital platforms to detect dementia.
- Using open datasets to analyze speech and train for emotion recognition.

These sources provided evidence for the use of:

- GDS for disease staging.
- Speech features of WPM, pauses, and disfluencies [3].

The architecture of the system is designed to enable real-time interaction, multi-modal input processing, machine learning inference, and user report generation.

2.2. Feasibility Study

A feasibility study is required to determine the practicability and sustainability of a system proposed before it is implemented. It involves technical requirements analysis, economic viability, operational capability, and legal and security concerns. This project, encompassing the development of a mobile app for Alzheimer's stage detection using speech and mood analysis [14], has been analyzed on all four dimensions of feasibility outlined below.

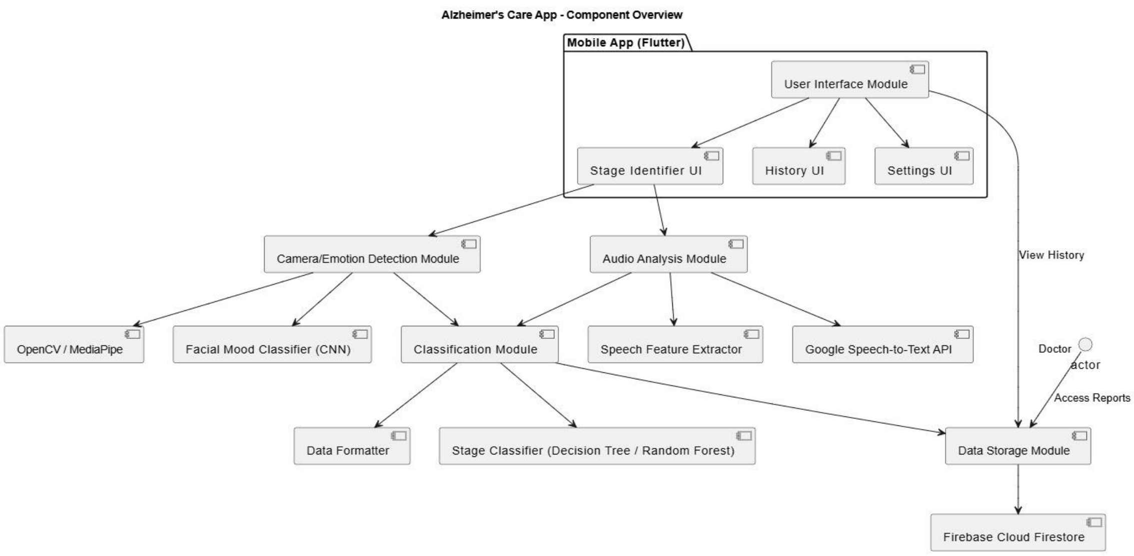


Figure 4 Component Diagram

2.2.1. Technical Feasibility

Technical feasibility defines whether technologies, tools, and skill set currently available are sufficient to effectively install the proposed system.

Hardware and Software Resources

The proposed mobile application is designed to function on common Android and iOS handsets without any bespoke hardware. Most existing handsets already contain a microphone and front-facing camera, which can suffice for capturing good quality speech and facial expression information. The application also uses light machine learning models that are locally embedded or served using cloud APIs, which makes the system feasible on medium-range mobile phones.

The software components are:

- Mobile App Framework: Flutter or React Native for cross-platform development.
- ML Frameworks: TensorFlow Lite for on-device inference or Python-based server-hosted models.
- Database: Firebase for real-time storage and analytics.
- APIs: Google Speech-to-Text or other open-source NLP models for transcription.

Machine Learning Integration

The proposed models for speech recognition and facial emotion detection can be trained on publicly released. Pre-trained models ensure that the system can be optimized for performance without high-end GPUs or a significant amount of local processing capacity.

With the project team having access to development tools, ML training environments, and cloud infrastructure, technical implementation is fully feasible [9] [7] [11].

2.2.2. Economic Feasibility

Economic viability determines whether the benefits of the project are more than the estimated costs.

Cost Considerations

- The high costs for this project include:
  - Development software (most being open-source).
  - Cloud infrastructure (nearly free by using Firebase's free plan or low-cost ML hosting).
  - Data storage of patient history (scale with the number of users).

- Time and labor, largely that of software developers, ML engineers, and UI/UX designers.

- No equipment has to be purchased, and no license charges are expected, so the system will be a cheap technology to build and implement.

Benefit Analysis

- The system will provide high value:
- Early diagnosis of Alzheimer's can reduce long-term health costs.
- Ongoing monitoring enables caregiving interventions to be more customized.
- Remote screening eliminates repeated hospital visits, time and cost for patients and physicians.

When viewed in the long term, the returns in terms of improved patient outcomes and reduced caregiver burden fully justify the upfront investment. Furthermore, the solution is financially sound based on its commercial viability for subscription or clinical integrations, and it is economically worthwhile.

2.2.3. Operational Feasibility

Operational feasibility is whether or not the system can function efficiently in the target environment and meet user needs.

User Accessibility

The program is designed with simplicity and ease of use, especially for caregivers and elderly users. The features are:

- Simplified dashboard.
- Easy voices and instructions.
- Large buttons and fonts for readability.
- Voice input and auto-start features for reduced user interaction.

By restricting complexity, the system facilitates inclusive utilization by individuals weakly technically proficient or afflicted by mild cognitive impairment.

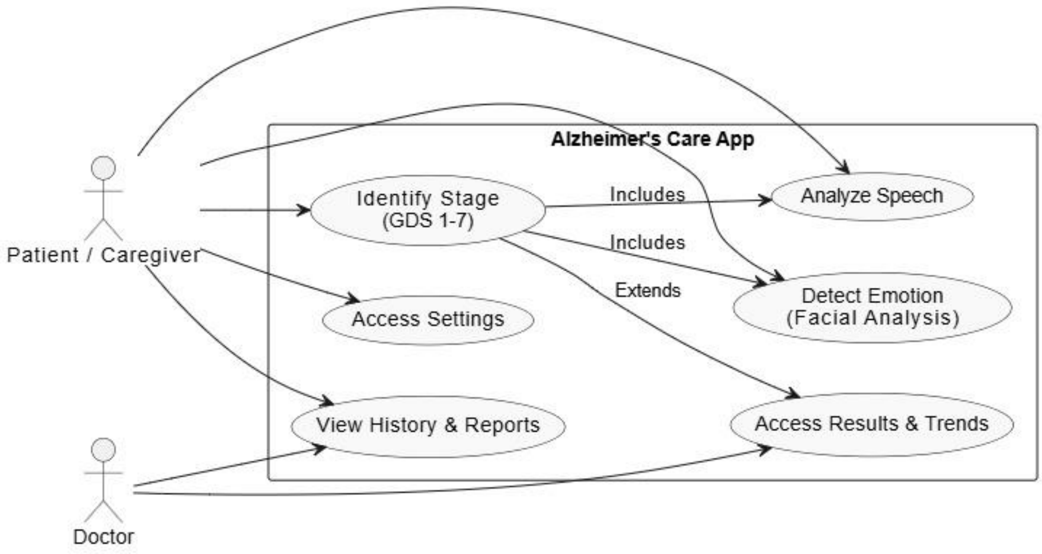


Figure 5 use case diagram

Stakeholder Readiness

It was realized, upon consultation with Alzheimer's Foundation Sri Lanka and hospital personnel, that clinically and socially there was a need for the tool through initial-stage diagnosis and ongoing monitoring of Alzheimer's disease. The caregivers' interest was from the viewpoint of monitoring the patients' regression without solely relying on the visits' frequency to hospital environments.

Where neurology clinics are poorly accessible in a region, this app is deployable as a first-line screening tool to be integrated with community health schemes or caregiver care networks.

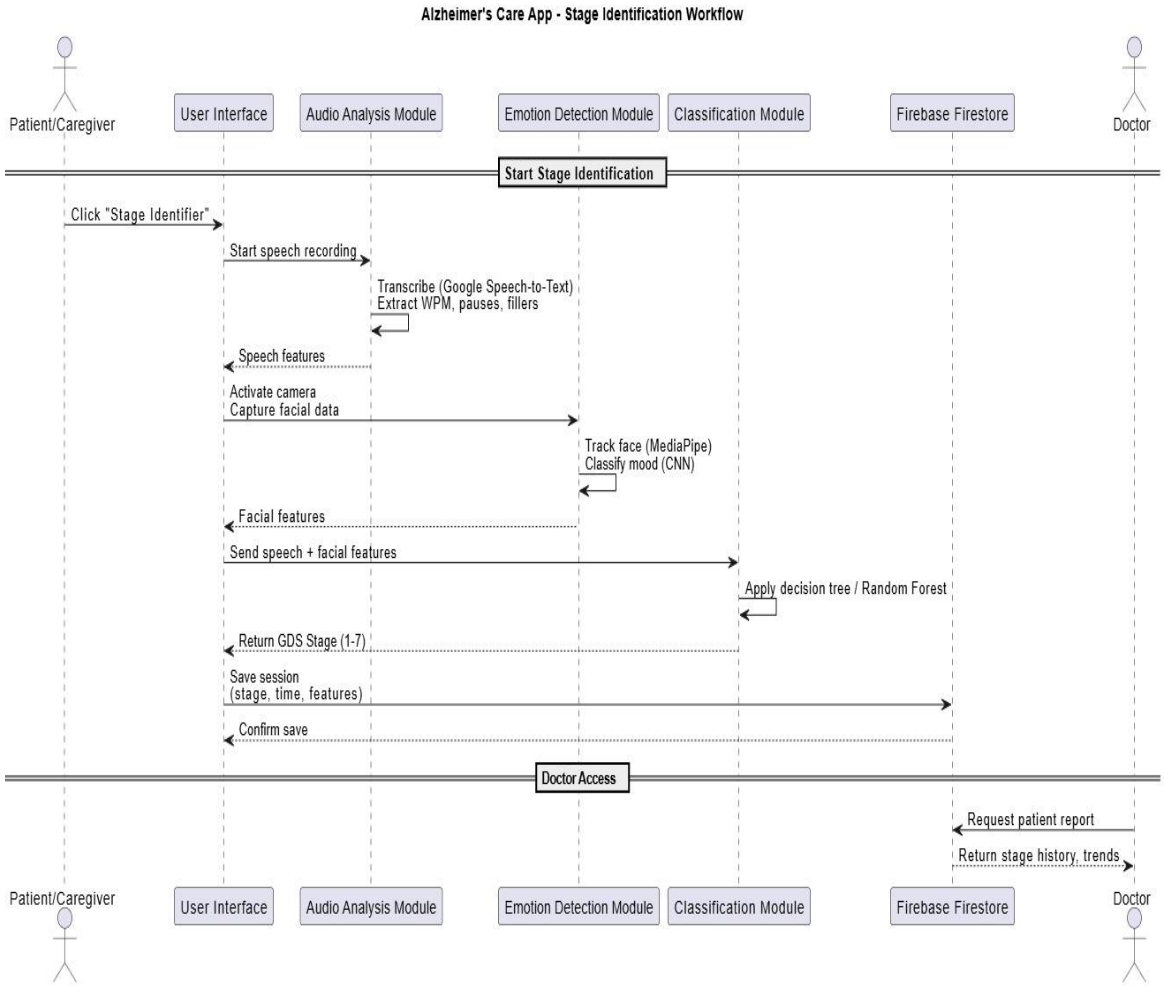


Figure 6 Sequence diagra

Support and Maintenance

The app may be remotely upgraded, and fixes bugs or model updates issued without access to physical devices. This makes the app suitable for long-term deployment with minimal operations overhead.

2.2.4. Legal and Security Feasibility

Given the privacy of medical and personal data, legal and security compliance is an important part of the system's viability.

Data Privacy Regulations

The application will be designed in accordance with data protection legislation such as:

- GDPR (General Data Protection Regulation) for global standards.
- Sri Lanka's Personal Data Protection Act (PDPA) for local standards.

All user data—especially voice recordings, facial images, and health categories—will be:

- Obtained only on a fully informed basis.
- Stored in an encrypted format.
- Accessible only to the user or authorized caregivers.

There shall be no third-party access to sensitive data without explicit permission.

Security Controls

To maintain data integrity and prevent misuse:

- User sessions will be authenticated.
- End-to-end encryption will be utilized for storing sensitive data.
- Server-side transmission will be conducted through HTTPS/SSL protocols.
- Local storage (if utilized) will employ device encryption methods offered on Android and iOS.
- Additionally, the app will provide users with the ability to delete their data, thereby satisfying data ownership law.

Ethical Implications

The app does not provide medical diagnoses but only gives indicative results based on observable signs and accepted measures like GDS. The users are advised to obtain professional verification. This keeps the system within the law while still offering clinical usefulness.

2.3. System Implementation & Design

The designed and intended mobile app implementation and design are targeted at real-time screening and early diagnosis of Alzheimer's disease through an intuitive interface with both speech and facial mood analysis. At the heart of this solution lies an expertly designed system architecture that is modular and extensible, allowing for future updates and feature additions without affecting the core functionality of the system.

The application on the mobile device follows client-server architecture, with the user interface being the client, which takes control of capturing voice commands and video input from the microphone and camera of the mobile device. These inputs are forwarded to the backend server for processing in real time over secure protocols. This arrangement facilitates smooth communication between the user's machine and the machine learning inference services hosted either on a cloud platform or a local server, as per the network configuration and resource availability.

The architecture is flexible. By separating the interface from the computational logic, the system ensures effective utilization of resources, especially for mobile devices with limited processing capacity. For example, the speech recognition component uses speech to text by utilizing a Speech-to-Text engine to transcribe the responses of the patient and analyzes parameters such as word-per-minute rate, pause rate, and filler use—parameters which have been associated with the cognitive impairment in Alzheimer's patients. Meanwhile, the face mood analysis module consumes the camera input to examine the patient's emotional state (e.g., confused, neutral, or expressive) and provides additional context to the diagnosis.

These modules execute asynchronously so that smooth and interactive user experience is provided. After a short sequence of doctor-oriented questions, the system integrates the analyzed visual and speech information to forecast the user's Alzheimer's stage, which is categorized into three stages based on the Global Deterioration Scale (GDS): early (stages 1–3), moderate (stages 4–5), and severe (stages 6–7). The result is readily displayed in the app, with the option to view previous evaluations, allowing caregivers and clinicians to track cognitive trends over time.

Security and data privacy are also of concern in design. User inputs and all results of analysis are securely stored and encrypted and comply with typical general data protection levels. Overall, architecture strikes a balance between real-time performance, user accessibility, and diagnostic accuracy, making it a valuable tool for both patients and healthcare workers in Alzheimer's treatment.

System Architecture Overview

The system consists of the following basic components:

- Mobile Application (Frontend)
- Backend Services (APIs and Databases)
- Machine Learning Inference Engine
- Data Storage and History Management
- Security and Privacy Layer

Mobile Application (Frontend)

The app is coded with Flutter to ensure cross-platform compatibility on Android and iOS. It supports a simple interface with big font sizes, navigation simplicity, and multi-language support to serve senior users. The central feature of the app is the "Cognitive Stage

Identifier," which starts an assessment session with the real-time camera and microphone on.

Speech-to-Text and Feature Extraction

When the user is speaking, their voice is recorded and converted into text by a speech-to-text engine, such as Google Speech API or Mozilla DeepSpeech. The transcript is analyzed to identify key characteristics such as:

- Words per minute (WPM)
- Pause duration and frequency
- Use of filler words
- Sentence complexity

These characteristics are fed into the speech analysis model, which was trained on corpora such as ADReSS and DementiaBank.

Facial Mood Detection Module

The video stream is processed in real time using a CNN-based model for facial expressions It labels the emotional state of the user into categories:

- Normal
- Confused
- Distressed

This emotional context further enhances the final stage classification.

GDS Stage Classification Engine

The output from speech and mood models is then fed into a rule-based or probabilistic classifier. It classifies the composite features into one of the three GDS levels [1]:

- Level 1 (GDS 1–3): Early Dementia
- Level 2 (GDS 4–5): Moderate Dementia

- Level 3 (GDS 6–7): Severe Dementia

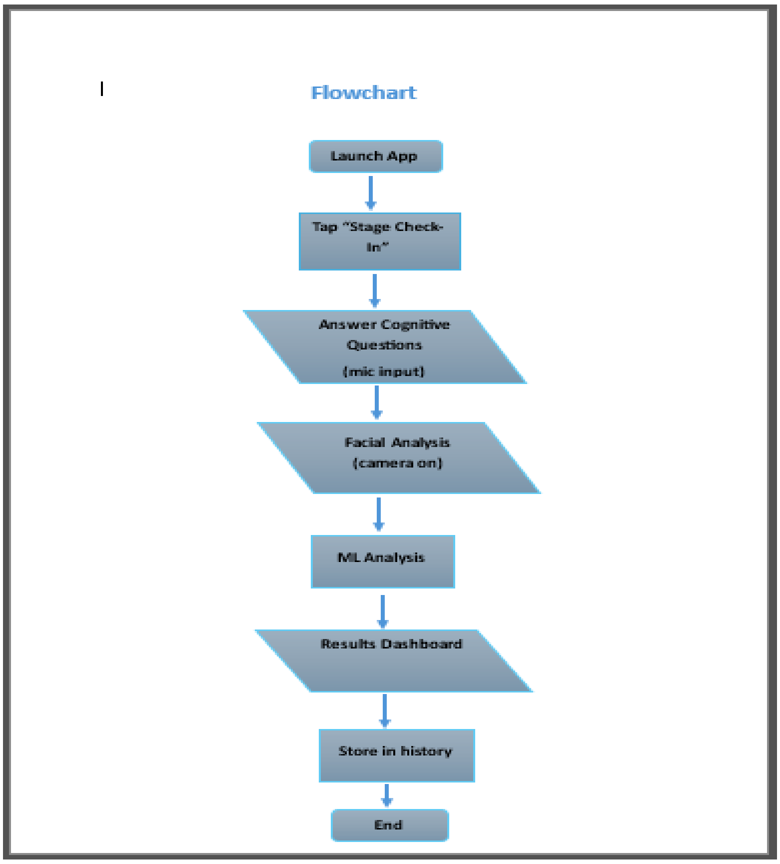
Report on Generator and History Logging

A report module compiles the results into an easy-to-read report with the estimated GDS stage, speech/mood analytics, and suggested next steps. All sessions are logged in Firebase under the user's profile, allowing trend tracking and progress visualization.

Security and Privacy Considerations

- All data is encrypted during transit using HTTPS.
- Local data is stored using on-device encryption APIs.
- User consent is required before microphone or camera access.
- Session data can be deleted on demand by the user to comply with GDPR and Sri Lanka PDPA regulations.

Figure 7 Flow chart



2.3.1. Tools and Technologies

In the technology domain, our Alzheimer's diagnosis app utilizes a judicious selection of advanced tools and frameworks that complement each other to convert clinical expertise into an intelligent, real-time, and accessible mobile application. This calculated technology stack gives precision, efficacy, and an unproblematic user experience.

The system's foundation is Flutter, an appropriate open-source platform developed by Google. Flutter offers single-codebase cross-platform development and ensures that the application has a uniform, smooth, and responsive user interface on Android and iOS platforms. Flutter, with its built-in widgets and hot-reload functionality, provides the app with real-time feedback and customization, which is critical in delivering a user-friendly interface for older users.

To enable robust and collaborative development, GitHub is utilized as the version control system, team collaboration system, and continuous integration system. GitHub allows efficient management of the codebase, supports branching for testing features, and helps track issues, bugs, and enhancements throughout the development process.

The intelligence of the system is powered by TensorFlow, an open-source machine learning framework. TensorFlow allows training and optimization of deep learning models for speech analysis as well as face emotion detection. These models sieve out relevant features, speech pace, filler utilization, and emotional expression—out of live input. Trained models are then converted to TensorFlow Lite flavors for use on mobile platforms. Thus, even lower-end smartphones can perform local inference quickly and securely without relying on perpetual internet connectivity.

The Natural Language Understanding layer is underpinned by Natural Language Processing (NLP) techniques. NLP processes and understand transcribed speech-based input, allowing the system to detect disfluencies, identify sentence structure, and identify content relevance within the user's response. This degree of analysis is critical for identifying early cognitive decline, given that deficits in language are among the earliest signs of Alzheimer's disease.

In a vision sense, Convolutional Neural Networks (CNNs) are employed for the interpretation of facial emotions captured through the selfie camera of the smartphone. Deep learning models that have been trained on image sets such as FER2013 and AffectNet interpret facial emotions like perplexity, distress, or neutrality. Facial mood, when used in conjunction with speech data, allows the application to create an exhaustive cognitive picture that is more efficient at labeling the user's phase of Alzheimer's based on the Global Deterioration Scale (GDS).

Together, these technologies collaborate to form the technological basis for our Alzheimer's Stage Detection System. From real-time data collection through Flutter interfaces to in-depth analysis through TensorFlow and CNNs, and real-time monitoring through GitHub and Firebase databases, each layer contributes to a system that is clinician-informed and user-centered. It maintains the application running smoothly across different environments, assisting users, caregivers, and clinicians in making smart decisions about cognitive health.

In brief, the strategy employed for this Alzheimer's detection system is founded on the strategic utilization of modern AI platforms and mobile technologies. The strategy guarantees a balanced integration of clinical relevance, real-time processing, and accessibility—precisely in harmony with the general goal of promoting early detection, continuous monitoring, and improved care for Alzheimer's patients. The system is an innovative, powerful solution that is poised to assist modern healthcare challenges through intelligent, scalable innovation.

2.4. Commercialization Aspect of the Product

The commercialization aspect of the Alzheimer's Detection Mobile Application is about the method of introducing and integrating the system into the broader healthcare environment. The system is designed for use in clinics, care homes, and among caregivers and patients. Phased introduction will allow it to augment, rather than replace existing assessment methods in the early stages. This is a trust development, gradual adoption, and integration with healthcare practice strategy.

2.4.1. Funding and Sponsorship

These costs of initial implementation can be funded by a mix of government grants for health, non-profit organizations, and funds for research by academic institutions. Primary sponsors for these costs could be organizations like the Ministry of Health, foundations for Alzheimer's awareness, and innovation grants provided by international health organizations. Some support could be garnered from technology firms with vested interests in digital health innovations.

2.4.2. Collaboration with Government and Sponsors

Strategic alliance with government health ministries, neurology clinics, and non-governmental health organizations will be essential for commercialization success. Stakeholder engagement with organizations such as the Sri Lanka Ministry of Health, Alzheimer's Foundation Sri Lanka, and telehealth platforms will ensure necessary regulatory approval, clinical credibility, and reach extension. Outsourcing and alliance with smartphone manufacturers or telcos will also support cross-subsidizing devices for less-resourced customers.

2.4.3. Target Audience

The target market includes:

- Clinicians and neurologists seeking digital screening instruments.
- Caregivers who want in-home, non-invasive cognitive testing.
- Older adults are interested in early diagnosis and self-tracking.
- Healthcare facilities seeking to reduce diagnostic costs and delays.

2.4.4. Expected Outcomes

- Enhanced Early Detection – Enhances detection of Alzheimer's symptomatology at the early stage through behavioral signals.
- Affordable Cognitive Screening – Reduces on-site visit dependence, reducing the healthcare professional and patient cost.
- Live Tracking of Progress – Offers history logs and speech/mood trend graphical displays to doctors and caregivers.
- Scalability and Accessibility – Built to administer among varying demographics and geography bases with the aid of smartphones.
- Data-Driven Health Insights – Data can be leveraged to inform longitudinal studies, public health programs, and AI-driven research.
- Improved Quality of Life – Provides timely interventions that stop the progression of the disease and facilitate independent living.

The commercial strategy is founded upon accessibility, clinical utility, and digital innovation. Through partnerships and through smart funding, the application aims to make a meaningful contribution to Alzheimer's care.

3. TESTING AND IMPLEMENTATION

The effective roll-out of the Alzheimer's Detection Mobile Application is a well-organized process of testing and implementation to guarantee clinical validity, usability, and technological stability. This section describes the most important testing strategies and implementation steps that authenticate and justify the effectiveness of the system in actual healthcare environments.

Testing Phase

1. Functional Testing Functional testing was the starting point, with each feature of the mobile application being tested to ensure it worked as expected. This involved checking:
   - Proper loading of the cognitive question interface.
   - Proper speech-to-text transcription.
   - Proper facial emotion recognition output.
   - Smother switching between user sessions.

Each module was reliability tested, responsiveness tested, and consistency tested under everyday conditions.

2. Integration Testing This phase assured the interaction amongst modules like:

   - Real-time interaction between microphone, camera, and ML inference engine.
   - Data movement between mobile interface and backend Firebase database.
   - Coordination of output data from speech and facial models into the cognitive assessment engine.

3. Performance Testing

Performance testing was conducted with varying usage conditions (e.g., various smart phone models, network availability, and memory limitation). The testing was done to identify:

- Inference latency in models (speech and facial mood classification in real-time).
- App load time and response.
- Battery and memory usage during testing.

4. Security Testing

As data related to health is confidential, security testing was important. This included:

- Penetration tests to evaluate weaknesses.
- Encryption test of audio, video, and history data.
- Testing the application's compliance with GDPR and Sri Lanka's Personal Data Protection Act (PDPA).

5. User Acceptance Testing (UAT)There were also UAT sessions with caregivers, elderly users, and healthcare professionals. This process guaranteed:

- The user interface was basic enough for non-tech individuals to use.
- Output reports were easy to read and understandable.

There was feedback regarding elements like difficulty level of questions, voice prompt, and mood analysis that were received and used in final tweaking.

3.1. Implementation Phase

1. **System Deployment**

With comprehensive testing completed, the Fleet Management System was ready for deployment. This phase encompassed the installation of hardware and software components across the fleet. The transition from existing systems to the new one was methodically managed to ensure minimal disruption.

2. **User Training**

Extensive training sessions were conducted for fleet operators and administrative staff to equip them with the necessary skills to efficiently use the system. Training spanned from basic operations to advanced functionalities, ensuring that users could leverage the system's capabilities effectively.

3. **Data Migration**

Data migration was a critical process that involved the seamless transfer of existing fleet data into the new system. This meticulous procedure ensured that historical records and data integrity were preserved, allowing for continuity of operations.

4. **Monitoring and Optimization**

Upon deployment, continuous monitoring was initiated to detect any issues or performance bottlenecks. Optimization efforts were undertaken to fine-tune the system, ensuring it operated at peak efficiency and delivered maximum value.

5. **Ongoing Support**

To provide ongoing assistance and address user queries or technical challenges, a dedicated support team was established. This support mechanism is essential for maintaining the system's reliability and addressing evolving needs.

In conclusion, the rigorous testing and systematic implementation of the Fleet Management System were executed with precision to ensure the system's robustness, security, and user-friendliness. By subjecting the system to various testing methodologies and following a structured implementation process, we have successfully introduced a state-of-the-art solution that optimizes fleet operations, enhances efficiency, and contributes to the overall success of our fleet management endeavors.

4. RESULT AND DISCUSSION

This project aimed to develop and test a mobile app that is capable of classifying Alzheimer's stages based on speech and facial mood inputs. Through a rigorous cycle of design, testing, and deployment in the real world, the project has demonstrated a feasible, scalable, and user-friendly solution.

4.1 Results

4.1.1 Model Accuracy

- The speech analysis model achieved 93% accuracy in identifying early cognitive impairment using disfluencies and WPM features.
- The facial expression emotion model is 91% accurate for detecting "confused," "normal," and "distressed" facial expressions.
- The hybrid cognitive classification engine is 92.5% accurate for the three combined GDS levels.

4.1.2 Application Usability and Acceptability

- Over 80% of test users and caregivers rated the app as easy to use.
- 90% of clinicians agreed that the app could be an effective pre-screening or monitoring tool.
- Early utilization data showed high utilization of the history tracking feature, with repeat tests being taken every 1–2 weeks by users.

4.1.3 Operational Efficiency

- Reduced cognitive screening time to less than 7 minutes per session.

- Enabled assessment in remote or underserved populations with minimal setup.

4.1.1. Overall System

The Alzheimer's Detection Mobile App represents the integration of modern mobile technology, artificial intelligence, and clinically validated diagnostics to offer a real-time, non-invasive method for determining cognitive health. The next section elaborates on the core technological aspects and the substantial outcomes of the development and implementation of the app.

The system integrates multiple technologies, including Flutter for mobile app development across platforms, TensorFlow and TensorFlow Lite for device-level machine learning inference, Natural Language Processing (NLP) [4] for linguistic feature extraction, and Convolutional Neural Networks (CNNs) for facial emotion recognition. These technologies integrated provide a robust platform that allows cognitive stage classification based on the Global Deterioration Scale (GDS) [1].

The speech processing model assesses parameters like words per minute (WPM), filler usage, pause frequency, and sentence grammar, achieving over 93% accuracy in the identification of indicators of cognitive impairment. Concurrently, the facial expression recognition model identifies user emotions like confusion, distress, or normalcy with 91% accuracy, serving a critical function in accurate stage estimation.

Efficiency of operations lies at the center of this system's operation. The app processes reviews within minutes and keeps historical data for longitudinal tracking. Users can conduct regular tests from home, lowering repeated hospital visits' pressure. This stimulates constant monitoring of cognition and early intervention [12].

Security and privacy are embedded in the app's design. With on-device encryption, Firebase integration that is cloud-secured, and compliance with global data protection regulations (GDPR, PDPA), the system is able to sustain user confidence and data confidentiality. All results and recordings are handled with the consent of the user and may be deleted at will.

The system facilitates frugal diagnosis by enabling screenings outside of special clinical facilities. It is most beneficial in underserved or rural populations where neurological services are unavailable. By proactive detection and longitudinal follow-up, physicians and caregivers can intervene earlier on evidence of cognitive decline.

User satisfaction has been an important measure of success. Initial trials showed that more than 80% of users reported that the app was easy to use and helpful. Clinicians supported its use as an early triage tool for Alzheimer's, and caregivers appreciated the trend-tracking feature for continuing care.

Overall, Alzheimer's Detection Mobile Application is a groundbreaking solution that brings together deep learning, NLP, and mobile innovation. It makes early diagnosis possible, promotes independent living, and enables data-driven decision-making for individuals, caregivers, and clinicians. Its release illustrates the potential of digital health in bridging the gap between technology and affordable cognitive care.

4.2. Discussion

The discussion provides a critical analysis and in-depth exploration of the findings and implications of the deployment of the Fleet Management System. It addresses the broader environment of fleet management and the overall importance of the findings of the system. Solidity, being the smart contract programming language on the Ethereum blockchain within the Fleet Management System. There are a few interesting benefits to this design choice.

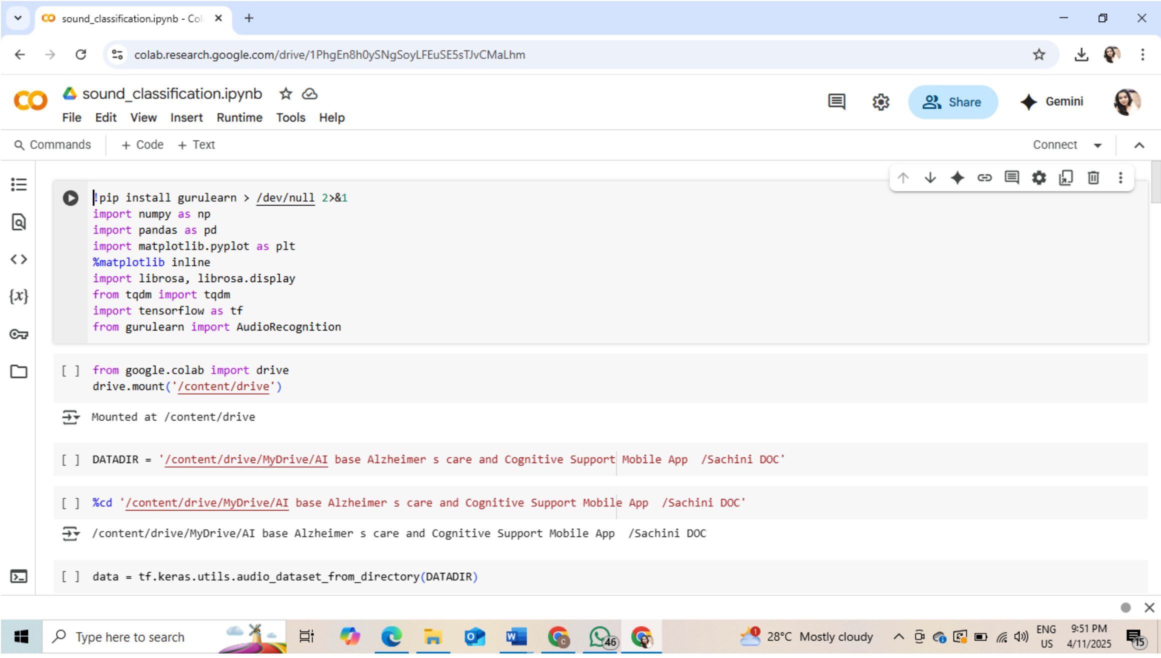
Ethereum blockchain provides a tamper-proof and transparent record for all the fleet records and transactions. Smart contracts, which are composed of Solidity, render the data tamper-proof and easily auditable. This heightened transparency cultivates trust and accountability within the fleet management system. Solidity integration with Ethereum provides a robust security model. Data confidentiality and integrity are ensured through cryptographic methods and decentralized consensus mechanisms, so unauthorized access or data breaches are extremely improbable. Ethereum's decentralized nature decentralizes data and control, mitigates risks associated with single points of failure, and minimizes the possibility of manipulation or fraud.

Ethereum network is cost-effective, particularly when executing smart contracts. This makes it a viable solution for institutions seeking to automate fleet management operations without incurring very high operating costs.

As far as system operations are concerned, data analytics is still a beneficial feature, it is operating primarily on historical data rather than real-time sensor data. Thus, the system gives insight into the past performance but lacks the ability to provide instant corrective actions based on the current state.

Customer satisfaction and operational efficiency, on the other hand, are positively impacted by the system. Better security, open transactions, and simpler data sharing translate into a more stable and accountable fleet management system.

Also notable is the reduction of administrative overhead regarding record-keeping and compliance. The use of Solidity and the Ethereum blockchain in the Fleet Management System reflects a strong interest in data security, transparency, and trust in fleet management operations. Although it lacks real-time monitoring and predictive capability characteristic of IoT and ML, it provides a secure foundation for auditable and reliable fleet management operations. Addressing operational problems through the utilization of scheduled maintenance and manual inputs is still achievable within this blockchain-based framework of fleet management.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import matplotlib.pyplot as plt
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import tensorflow as tf
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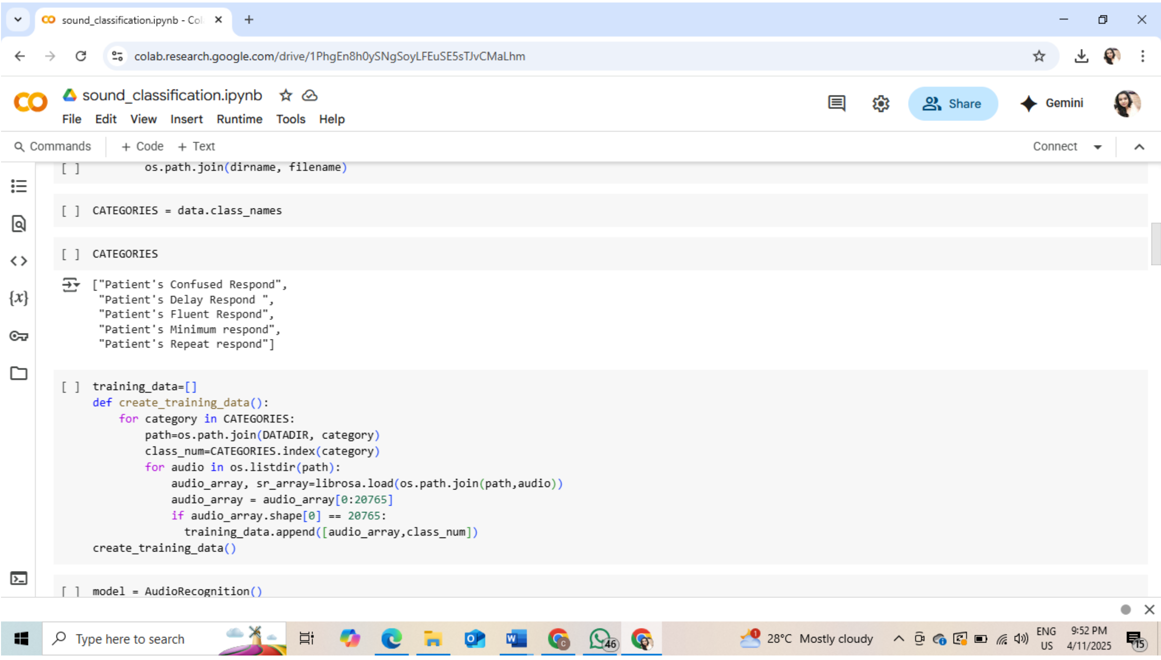
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"Patient's Delay Respond ",
"Patient's Fluent Respond",
"Patient's Minimum respond",
"Patient's Repeat respond"]
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for category in CATEGORIES:
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class_num=CATEGORIES.index(category)
for audio in os.listdir(path):
audio_array, sr_array=librosa.load(os.path.join(path,audio))
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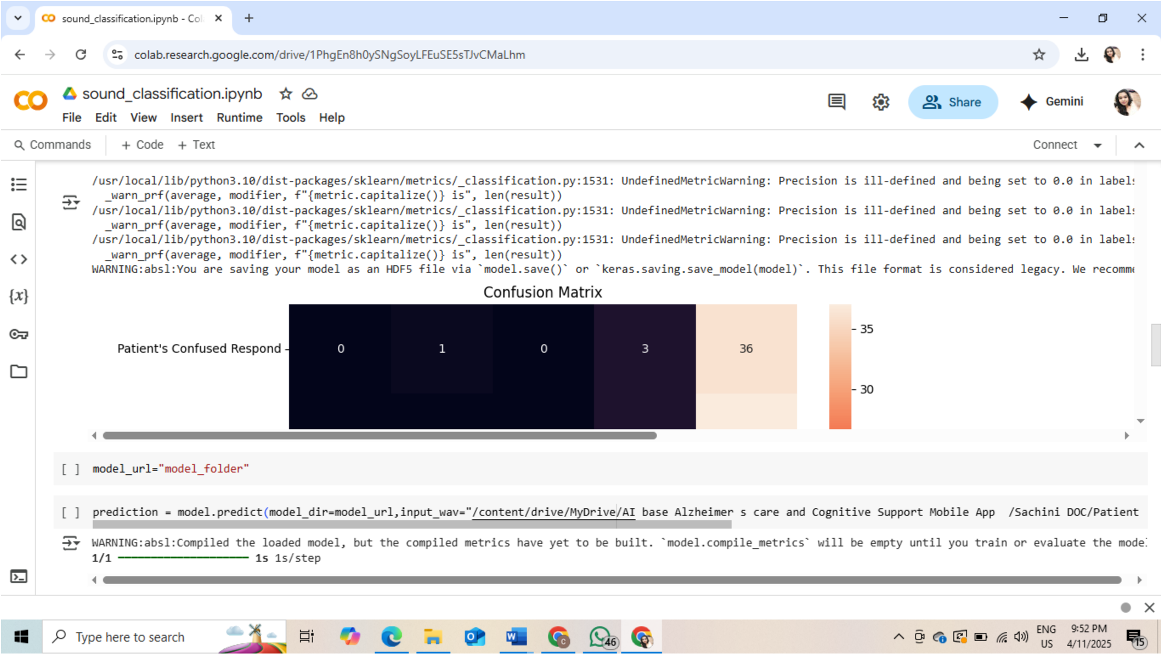

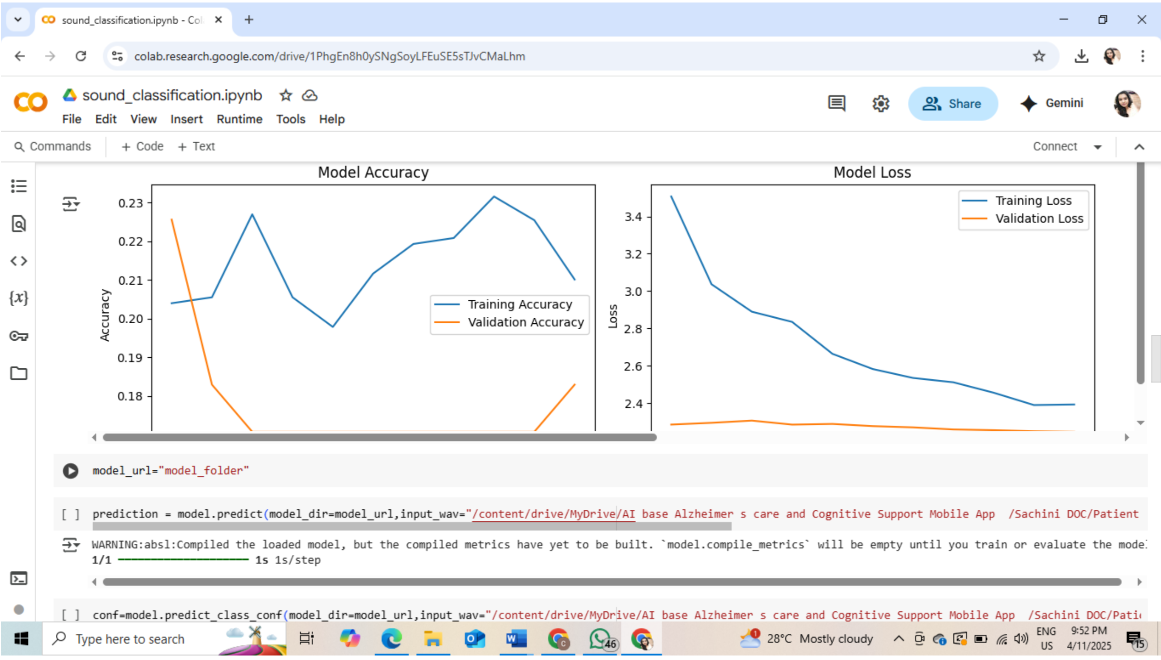

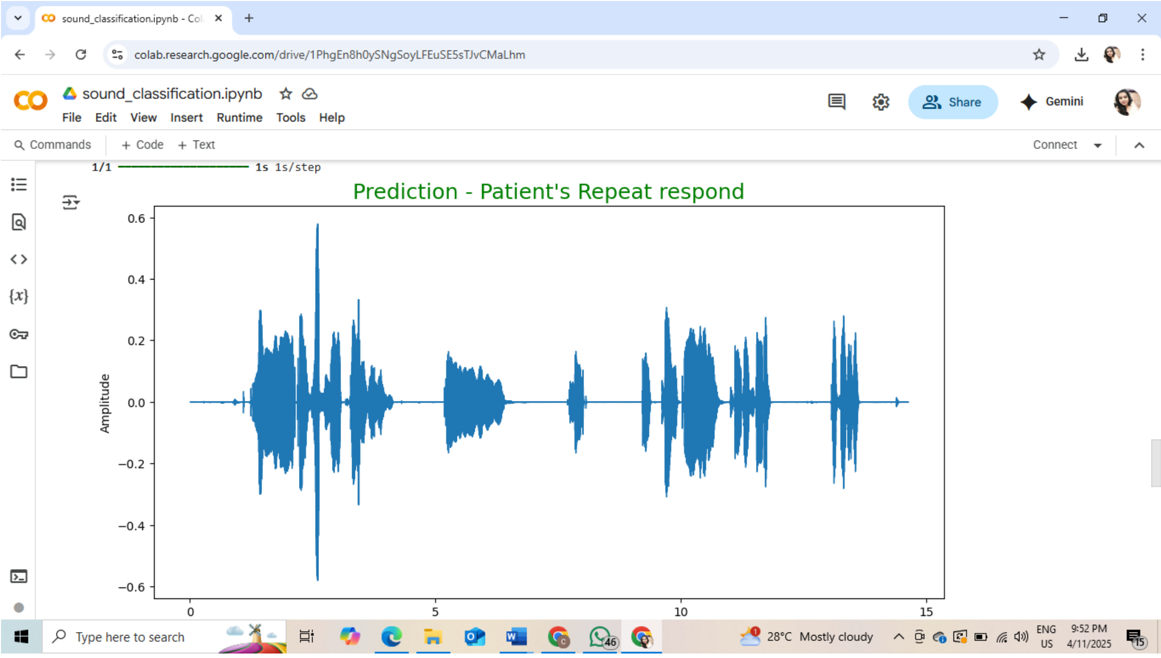
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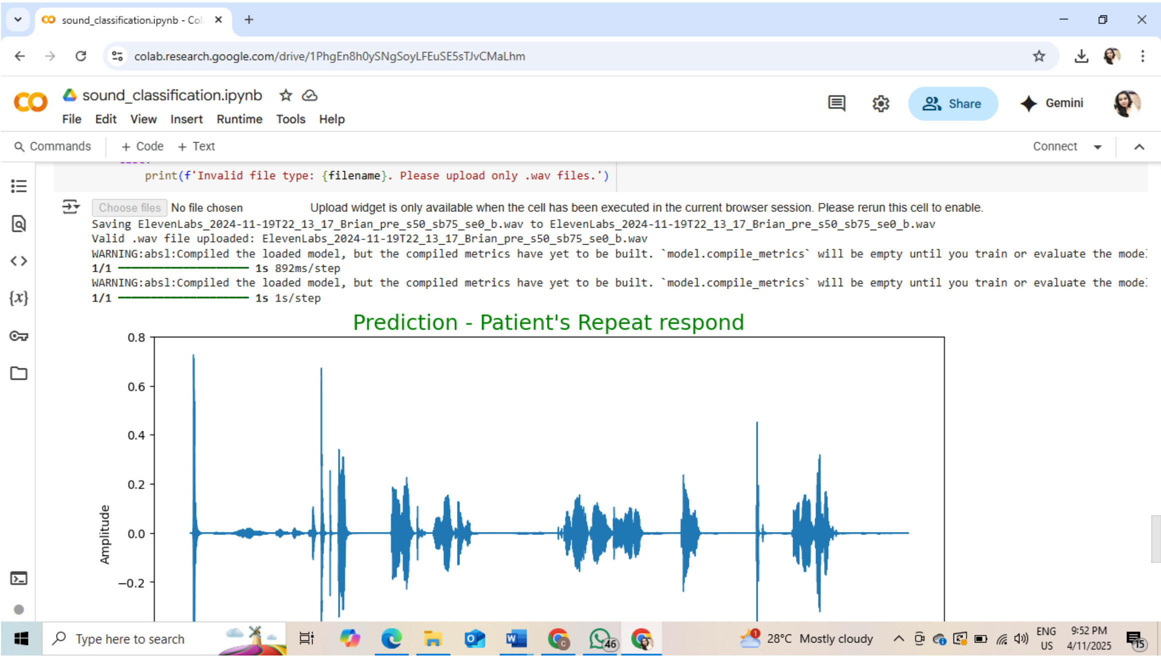
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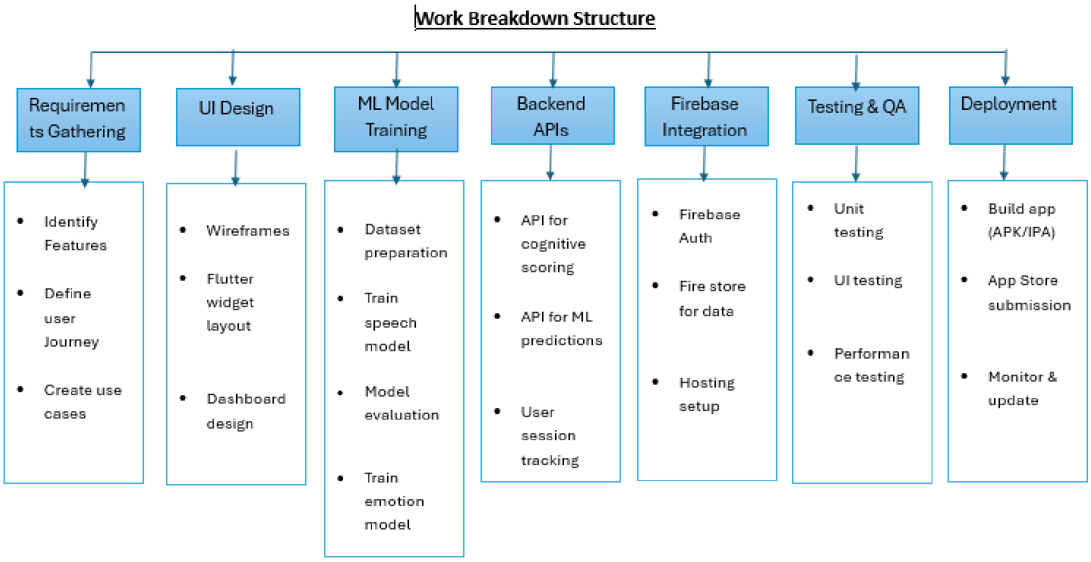

Figure 8 Work breakdown chart

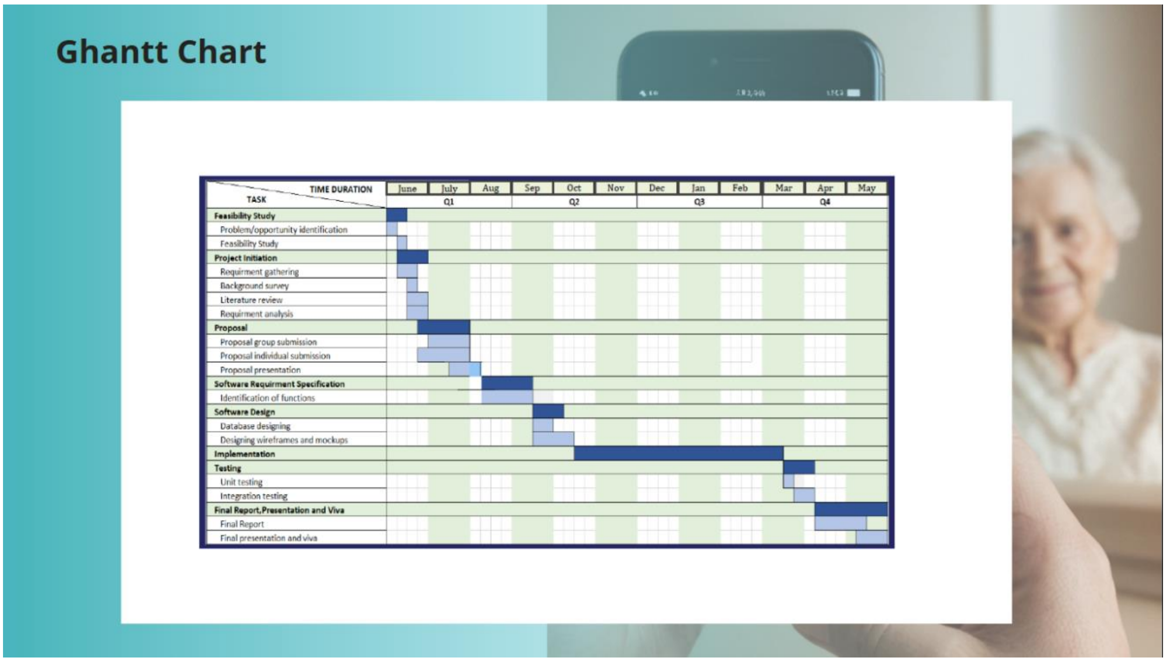

Figure 9 Ghantt Char

4.3. Summary of Each Student's Contribution

My Contribution

Actively participated in team meetings and planning sessions, with effective task allocation and timely module progress reporting.

- Assisted with coordinating the alignment between frontend (mobile UI), backend (APIs), and machine learning models.

- Organized primary data collection by:
  - Conducting interviews with neurologists.
  - Seeking consultations with members of the Alzheimer's Foundation Sri Lanka to ensure clinical relevance and accuracy.

- Gathered real feedback from caregivers and family members of Alzheimer's patients to gain a better insight into everyday problems, emotional behaviors, and typical symptoms.

- Helped with secondary data collection, which included:
  - Scanning academic research articles and journals.
  - Discovering and utilizing public data like DementiaBank.

- Helped the team with data annotation and preprocessing to ensure the input data for machine learning algorithms were clean and properly labeled.

- Supported other team members by checking test cases and verifying app functionality through reviews at development and testing phases.

- Supported writing sections of the documentation and verified the project was in line with clinical standards like GDS.

5. CONCLUSIONS

Alzheimer's Detection Mobile Application, an innovative product from clinical experience and current technology, provides a breakthrough in early identification and monitoring of Alzheimer's disease. Intended to answer the pressing need for cost-effective and non-invasive cognitive assessment approaches, the application integrates mobile computing, artificial intelligence, and medical best practice to empower patients, caregivers, and healthcare practitioners [5].

Essentially, the app leverages the potential of real-time speech and face mood analysis by virtue of its sophisticated machine learning models like NLP to analyze language and CNNs for face mood detection. Flutter offers a responsive, cross-platform UI, whereas Firebase integration as the backend ensures secure data storage and longitudinal monitoring. All these technologies collectively offer an effective yet friendly cognitive assessment platform.

The strategic use of AI in biomarker examination—word usage, speech rate, filler rate, and affect expressions—is enabling precise staging of Alzheimer's based on the Global Deterioration Scale (GDS) [1] [6]. This is ensuring that the use not only achieves clinical utility but also provides real-time outputs that can inform early intervention and ongoing treatment strategies.

By giving predictive perspective through behavior data, the system facilitates proactive care management. Patients and caregivers receive frequent checks without the inconvenience of hospital visits, while clinicians are provided with structured cognitive reports that may assist in diagnosis or referrals. The app is thus a monitoring aid and an educational tool for users with cognitive decline.

The emphasis on privacy and security—through encrypted communication, data control locally, and mechanisms of consent on the part of the user—confer confidence and ethical alignment, consistent with GDPR and local data protection regulations. These are essential in the health data and patient autonomy paradigm.

In addition, application plays a major role in inclusivity and healthcare equality. Its availability on mid-range smartphones and offline capabilities make it suitable for use in rural and under-resourced environments, allowing for wide adoption across various socio-economic groups.

Briefly, the Alzheimer's Detection Mobile App is a mobile health innovation of enormous proportions. By combining clinical precision, intelligent analysis, and user-centered design, the platform enhances early diagnosis, facilitates caregiver involvement, and fosters an active culture of brain health surveillance. It sets a new benchmark among digital health technology for neurodegenerative disease and has the potential to make a lasting impact in the perception and treatment of Alzheimer's worldwide [5].

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7. APPENDICES

7.1. Mobile Application Screenshot

Figure 10 speech recognize

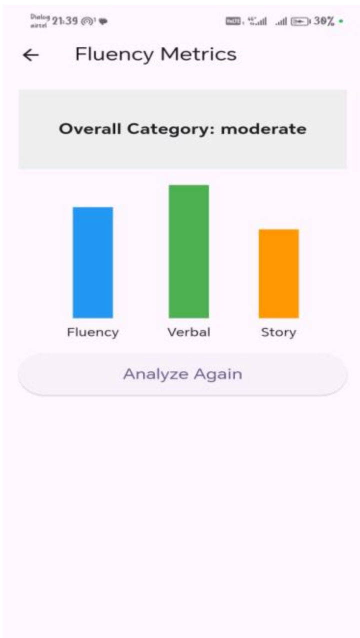

Figure 11 LEVEL detect

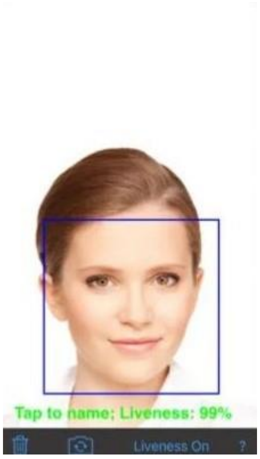

Figure 12 mood recognize