# AI-Based Early Detection of Alzheimer's Disease Using Speech Analysis


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# 1. Introduction

Alzheimer's Disease (AD) is the most prevalent form of dementia, severely impacting cognitive functions, memory, and communication abilities. Dementia, particularly AD, poses a critical global health challenge, with the number of affected individuals projected to exceed 139 million by 2050 [1]. AD manifests subtly in its early stages, with symptoms such as mild memory loss, language difficulties, and attention deficits, which progressively lead to severe cognitive dysfunction and loss of independence. Early detection of AD is paramount as it allows for interventions that can slow disease progression and enhance the quality of life for patients [2].

The economic burden of AD is substantial, with healthcare costs and caregiving expenses escalating as the disease progresses. Early detection not only benefits patients and their families by providing more time for planning and intervention but also alleviates the financial strain on healthcare systems [3]. Traditional diagnostic methods, while effective, are often invasive, expensive, and impractical for large-scale screening. This necessitates the exploration of non-invasive, cost-effective alternatives that can be easily deployed across diverse populations.

In recent years, advancements in Artificial Intelligence (AI) and machine learning have opened new avenues for diagnosing AD through non-invasive means. Among these, speech analysis has emerged as a promising approach to detect Mild Cognitive Impairments (MCI) indicative of early-stage AD. This report explores the development of an AI-based system that leverages deep learning to analyze speech data for the early detection of Alzheimer's Disease. The proposed system aims to provide a scalable, cost-effective, and user-friendly solution to address the growing demand for early AD detection.

# 2. Existing Methods

Diagnosing Alzheimer's Disease (AD) currently relies on interviews, cognitive tests, brain imaging, and blood tests. These methods are invasive, time-consuming, and often detect AD only after significant progression, reducing treatment effectiveness [4]. With the global prevalence of dementia and AD rising, existing diagnostics are increasingly strained, highlighting the urgent need for scalable, efficient solutions.

Advancements in Artificial Intelligence (AI) and machine learning offer promising opportunities for developing non-invasive, effective diagnostic techniques for neurodegenerative diseases. With new studies suggesting Dementia symptoms may appear up to 18 years before current diagnostic methods can identify them [4] speech analysis is becoming particularly promising. Individuals with AD exhibit changes in speech patterns—such as increased hesitation, reduced fluency, and simplified sentence structures [5]—which AI models can analyze to differentiate between healthy aging and early cognitive decline.

**DemensAI**, a startup founded by DTU students, leverages AI tools, including large language models, to analyze speech's acoustic and linguistic features. Their models detect subtle voice changes indicative of dementia, achieving 93% accuracy and providing results in just 2 minutes—significantly faster than existing tests.

| **Aspect** | **Conventional** | **AI Model** |
|---|---|---|
| Invasiveness | Invasive | Non-Invasive |
| Cost | High | Low |
| Scalability | Limited | High |
| Time | Lengthy | Rapid (2 min) |
| Accessibility | Clinical settings | Smartphones |
| Monitoring | Not feasible | Continuous |

Table 2.1: Comparison of Conventional vs. AI-Based Methods

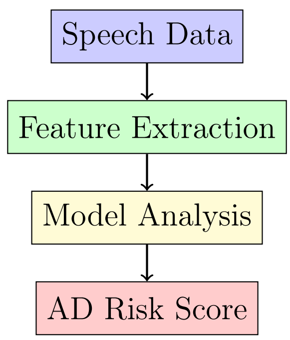


Figure 2.1: AI-Based Speech Analysis Workflow

AI and machine learning, particularly through speech analysis, offer a non-invasive, cost-effective, and scalable alternative for early AD detection. Collaborations with innovative startups like DemensAI can enhance the development of effective diagnostic tools, addressing the growing global burden of AD.

# 3. Dataset

A major factor in our intelligent system proposal is acquiring sufficient, high-quality data samples. The quality of the dataset is critical in the machine learning process, significantly impacting how the model is trained and performs. Unlike neuro-imaging, publicly accessible speech data is limited.

## 3.1 Types of Speech Data

Speech data for the analysis of cognitive impairment can be categorized into several types, as shown in Table 3.1.

| **Type** | **Description** |
|---|---|
| Picture Description | Describing images presented |
| Verbal Fluency | Generating words under constraints |
| Story Recall | Recalling stories after hearing them |
| Sentence Construction | Forming sentences from prompts |
| Repetition | Repeating words or phrases |
| Free Conversation | Natural, spontaneous speech |

Table 3.1: Types of Speech Data for Cognitive Impairment Analysis [6]

Our proposed intelligent system utilizes **Free Conversation**, which best matches day-to-day language detectable by an app running in the background.

## 3.2 Existing Datasets

Table 3.2 summarizes some commonly used Free Conversation speech datasets currently available.

| **Dataset** | **Description** |
|---|---|
| Carolina Conversations Collections [6] | Over 400 conversations with older adults from diverse ethnic b |
| Multimodal Dementia Corpus [6] | 101 hours of speech data collected longitudinally |

Table 3.2: Existing Free Conversation Speech Datasets

While Free Conversation is valuable, the lack of fully standardized tasks across datasets can make comparative analysis and model training challenging. Hence, a lack of sufficient

datasets is a prominent limitation in advancing the diagnosis of Alzheimer's disease through speech analysis.
Insufficient data can lead to overfitting. This has been shown in small-sample AD diagnosis studies where the accuracy has declined as sample size increases [7], suggesting an overestimation of model performance. This overestimation can create unrealistic expectations and pose risks in deploying clinical speech analytic models.

## 3.3 Key Considerations for Collection

When collecting a dataset for our model, several factors need to be considered, as outlined in Table 3.3.

| **Consideration** | **Details** |
|---|---|
| Longitudinal Design | Collect data over time to track disease progression |
| Diverse Participant Pool | Balance age, gender, race, ethnicity, and language |
| Large Sample Size | Multiple voice recordings per participant |
| Varied Dementia Types | Include other forms for accurate AD detection |
| Varied AD Stages | Include participants at different disease stages |
| Standard Labeling | Label samples with cognitive status and AD presence |
| Privacy | De-identification, consent, data encryption (see Section 6) |

Table 3.3: Key Considerations for Dataset Collection

Protecting participant privacy is crucial. Practices such as de-identification, obtaining informed consent, and data encryption will be followed.

By focusing on expanding existing datasets through collaboration and adhering to key considerations in data collection, we aim to build a robust dataset for training our model. This approach addresses limitations such as overfitting and ensures ethical standards are maintained.

# 4. Design and Implementation

The design and implementation of our AI-based early detection system for Alzheimer's Disease (AD) integrates advanced machine learning techniques, robust data preprocessing, and efficient system architecture. This chapter details the methodologies and system components essential to achieving accurate and efficient AD detection through speech analysis.

## 4.1 Machine and Deep Learning Methods

Our system leverages state-of-the-art Transformer-based architectures for analyzing speech data. The speech data will be made using both acoustic and linguistic features to improve the system's ability to accurately detect AD. Transformers have revolutionized natural language processing (NLP) and speech analysis by introducing self-attention mechanisms, enabling efficient and accurate modeling of sequential data [8].

### 4.1.1 Transformer-Based Architecture

The Transformer architecture incorporates key components, including:

- **Self-Attention Mechanism:** Enables the model to weigh the importance of different parts of the input sequence, focusing on patterns indicative of cognitive decline.
- **Positional Encoding:** Represents the order of words or sounds, ensuring the sequence information is preserved despite parallel processing.
- **Scalability:** Transformer models process entire sequences simultaneously, leading to faster computation and greater scalability for large datasets.

### 4.1.2 Model Evaluation

An important consideration in our model is the decision threshold, which determines the balance between false positives and false negatives.

| Threshold Adjustment | Effect on False Negatives | Effect on False Positives |
|---|---|---|
| Lowering the threshold | Reduced | Increased |
| Raising the threshold | Increased | Reduced |

Table 4.1: Effects of Threshold Adjustment on Model Classification

This balance is crucial, especially in the context of Alzheimer's Disease (AD), where false negatives can give a false sense of security, delaying early intervention that could protect neurons and mitigate disease progression. However, false positives can also have severe psychological and social impacts on patients and their families, highlighting the need for further discussions with healthcare professionals and patients to determine the optimal threshold.

### 4.1.3 Data Preprocessing and Feature Extraction

The preprocessing pipeline (Fig. 4.1) prepares raw speech data for analysis by applying a series of transformations. Noise reduction filters background noise, normalization ensures consistent audio levels, segmentation divides speech into manageable intervals, and feature extraction identifies key acoustic and linguistic markers. This streamlined process enhances model accuracy by ensuring high-quality input data.

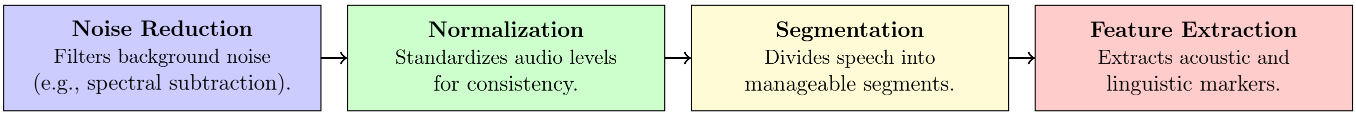


Figure 4.1: Preprocessing Pipeline for Speech Data with Annotations

## 4.2 System Architecture

The system architecture employs a hybrid approach, integrating edge and cloud computing to ensure scalability, low latency, and enhanced privacy. This design facilitates efficient data processing and real-time inference while maintaining stringent data protection standards.

### 4.2.1 Edge Computing

Speech data is preprocessed locally on user devices, reducing latency and enhancing privacy by minimizing data transmission. Lightweight Transformer variants, such as MobileBERT, perform initial analysis directly on the device. This allows for rapid detection of potential AD indicators without relying on continuous cloud connectivity.

### 4.2.2 Cloud Computing

The cloud infrastructure handles advanced model inference, extensive data storage, and large-scale analysis. By centralizing these processes, the system benefits from robust computational resources and facilitates collaborative insights for healthcare providers. Data synchronization between edge devices and the cloud ensures that comprehensive analyses are available for clinical evaluation and long-term monitoring.

Table 4.2: Comparison of Cloud and Edge Computing

| Aspect | Cloud Computing | Edge Computing |
|---|---|---|
| Data Processing | Centralized, scalable processing | Local, real-time preprocessing |
| Privacy | Requires secure transmission | Enhanced, as data remains on device |
| Scalability | High | Limited by device resources |

Given these factors, adopting a hybrid approach that combines edge and cloud computing, where audio is pre-processed on edge devices before being transferred to the cloud, emerges as the most suitable solution for the AD detection app. This strategy leverages the strengths of both paradigms, creating a robust, scalable, and secure system for early detection of Alzheimer's disease. By efficiently processing data locally, it reduces latency and enhances user privacy, while the cloud infrastructure supports large-scale data analysis and storage. This hybrid model ensures efficient data processing while maintaining user privacy and regulatory compliance.

### 4.2.3 Smart Homes and IoT Integration

Integrating IoT devices, particularly smart speakers (e.g., Alexa, Google Home), enhances the system's accessibility by enabling continuous, non-invasive speech monitoring. These devices provide reliable speech recognition and signal processing capabilities, crucial for capturing high-quality acoustic data [9]. Their stationary nature and always-on functionality make them ideal for health applications, allowing for passive data collection without requiring active user participation.

Smart speakers transmit processed speech data securely to the cloud for further analysis, ensuring compliance with medical IT standards. Additionally, expanding into wearable technologies, such as smartwatches, can capture complementary health metrics (e.g., heart rate, activity levels), providing a holistic view of the user's health status.

## 4.3 Sensor Technologies

The primary sensor in our system is the smartphone microphone, which captures high-quality acoustic data essential for speech-based diagnostic models. Advances in Micro-Electro-Mechanical Systems (MEMS) microphones have enhanced sensitivity, noise suppression, and frequency range detection, making them reliable for continuous health monitoring.

Secondary sensors, including accelerometers and gyroscopes, detect and filter out noise caused by user movement, improving the precision of speech data analysis. Advanced sensor fusion techniques, such as Consensus-Based Kalman Filtering, integrate motion data with audio processing to enhance noise reduction and contextual understanding [10]. This ensures robust data collection across diverse environments and smartphone models, maintaining consistency and reliability in diagnostic outputs.

## 4.4 User Story Map

The user story map for the AI-based AD detection app outlines the key features and functionalities of the app from a user (patient) perspective.

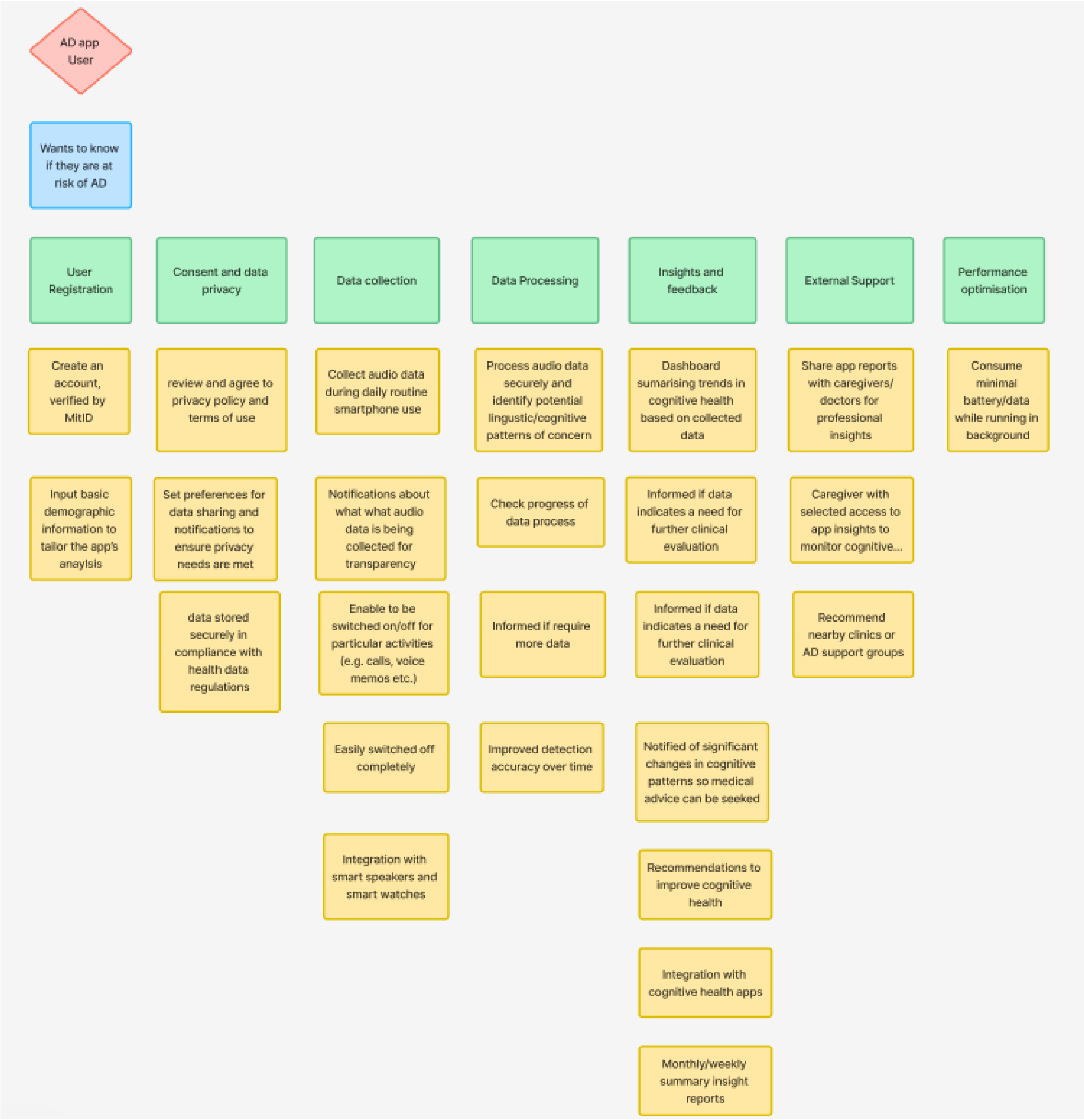


Figure 4.2: User Story Map for the AI-Based Alzheimer's Detection App using Figma [11]

This chapter delineates the comprehensive design and implementation strategies for our AI-based Alzheimer's detection system. By integrating advanced machine learning techniques, robust data preprocessing, scalable hybrid architecture, and innovative IoT solutions, the system offers a reliable and accessible tool for early AD detection.

# 5. Business Plan

The introduction of benchmarks like ADReSS [12] and ADReSSo [13] has advanced Alzheimer's research significantly. aligning our app with these benchmarks ensures reliable AI training., improves diagnostic accuracy, and facilititates clinical adoption

## 5.1 Three-Week Implementation Plan

The plan focuses on developing a functional prototype in three weeks, ensuring efficient resource allocation.

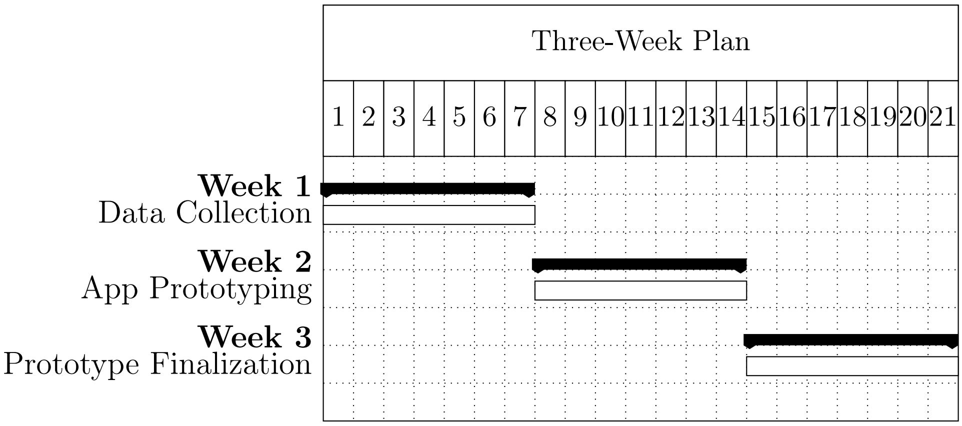


Figure 5.1: Three-Week Implementation Gantt Chart

Table 5.1: Three-Week Implementation Plan

| **Week** | **Focus** | **Activities** |
|---|---|---|
| Week 1 | Data Collection | Gather datasets, annotate for AD-specific features, and ensure ethical compliance. |
| Week 2 | App Prototyping | Train AI models, design the interface, and integrate security measures. |
| Week 3 | Prototype Finalization | Conduct testing, gather stakeholder feedback, and refine the system. |

### 5.1.1 Integrated Screening and Marketing Strategy

Our app offers a non-invasive AD screening tool, complementing biomarker-based blood tests for early diagnosis. Together, these tools form a multi-step decision framework for timely intervention and imporved diagnostic accuracy [14].

Table 5.2: Target Consumer Segments

| Segment | Description |
|---|---|
| Healthcare Professionals | Non-invasive diagnostic aid for neurologists, geriatricians, and primary care physicians. Supports early detection and integrates with EHR systems for enhanced analytics. |
| Individuals at Risk | Accessible app for elderly users and those with a family history of AD. Offers personalized insights, progress tracking, and medical recommendations. |

### 5.1.2 Change Management: ADKAR Framework

To ensure effective adoption in healthcare, the ADKAR model provides a structured framework for transitioning from traditional methods to AI-powered diagnostics.

| ADKAR Stage | Application in AI-Based Alzheimer's Detection App |
|---|---|
| **Awareness** | Communicate the need for AI-based systems, emphasizing limitations of traditional methods and benefits like early detection. |
| **Desire** | Highlight personal and professional advantages, fostering support among users and stakeholders. |
| **Knowledge** | Provide training on system functionality, results interpretation, and workflow integration |
| **Ability** | Equip users with necessary skills through workshops and offer ongoing technical support |
| **Reinforcement** | Regularly monitor adoption, reward usage, and refine the system based on feedback. |

Table 5.3: ADKAR Framework for AI-Based AD Detection

By aligning with medical benchmarks, leveraging participatory design, and utilizing structured change management, the project aims to revolutionize early AD detection. Strategic implementation and targeted marking ensure adoption and scalability, leading to improved diagnostic efficiency and patient outcomes.

# 6. Discussion

Despite extensive research in the area, detection of AD through AI remains challenging with several limiting factors which need to be considered.

## 6.1 Limitations

### 6.1.1 Data Scarcity and standardised datasets:

An advantage of using free conversation data is the abundance of datasets comprising normal speech, which can be leveraged to train and fine-tune transformer-based models. However, the challenge lies in the limited availability of diverse, Alzheimer's-specific, data sets. With the current data available, we can utilize the extensive normal speech datasets to pre-train our model, enabling it to understand general language patterns and nuances. Subsequently, we can fine-tune the model using the limited Alzheimer's data available; however, we risk overfitting and reduced generalizability.

To ensure our model is highly accurate, a straightforward solution to addressing the data scarcity in Alzheimer's-specific conversational data is by collecting new data. However, this approach requires considerable time, financial investment, and resource allocation. Taking a collaborative approach could make this solution more viable. Given the growing interest in this area, particularly due to the aging population, partnering with other organizations and research institutions could help create a more extensive and diverse database. By pooling resources and data, we can enhance the robustness and generalization of our model. Collaborative efforts could involve sharing anonymised conversational datasets, co-developing data collection protocols, and conducting joint research studies.

Additionally, leveraging **synthetic data generation** and **data augmentation** techniques can significantly expand the amount of training data. Methods such as generative adversarial networks (GANs), data perturbation, and oversampling can be employed to create synthetic conversational data that mimics real-world scenarios. These techniques help avoid overfitting by introducing variability and diversity into the training dataset,

### 6.1.2 Privacy concerns:

The integration of machine learning in healthcare, particularly using voice and speech data for detecting Alzheimer's disease (AD), is significantly limited by ethical and privacy concerns. Patient confidentiality and data usage must be carefully considered to ensure trust and compliance with regulations.

It is mandatory that we adhere with health data guidelines and regulations and have secure systems in place monitoring on who has access to the data, how it is stored, and when and how it is safely destroyed. They key regulations which would need to be adhered to are:

- General Data Protection Regulation (GDPR): For projects involving data from European Union (EU) citizens, GDPR is essential. It mandates strict data protection and privacy rules, including obtaining explicit consent from individuals before collecting their data, ensuring data minimization, and allowing individuals to access and delete their data2

- European Health Data Space (EHDS): he EHDS is a health-specific data sharing framework that establishes clear rules, common standards, and practices for the use of electronic health data. It aims to facilitate the secure and ethical sharing of health data for care, research, and innovation while ensuring patient privacy and data protection

- National Regulations:In Denmark, the Danish Data Protection Act supplements the GDPR and provides additional guidelines specific to the handling of personal data within the country. This includes specific provisions for health data and the responsibilities of data controllers and processors.

| Stage | GDPR Considerations for AI-Based Alzheimer's Detection App |
|---|---|
| **Capture** | - Capture audio recordings and personal data necessary for detecting Alzheimer's disease<br>- Collect data lawfully, fairly, and transparently using secure methods<br>- Inform users about data collection purpose, usage, and their rights<br>- Obtain explicit consent from users, documented and revocable<br>- Allow users to set preferences for data sharing and notifications |
| **Store** | - Store data securely with encryption and access controls<br>- Use GDPR-compliant cloud environments within the EU or in countries with adequate data protection laws<br>- Ensure third-party compliance with GDPR<br>- Implement a data breach response plan and notify affected individuals and authorities within 72 hours<br>- Ensure compliance with health data regulations |
| **Use** | - Use data solely for detecting Alzheimer's disease and providing insights to healthcare professionals<br>- Do not use data for unrelated purposes without explicit consent<br>- Provide transparency by notifying users about what data is being collected and for what purpose<br>- Allow the system to be easily switchable on and off for particular activities (e.g., calls, voice memos) |
| **Destroy** | - Retain data only as long as necessary for the collected purpose<br>- Define clear retention periods based on medical and legal requirements<br>- Securely delete data when no longer needed, ensuring irretrievable deletion |

Table 6.1: GDPR Information Life Cycle for AI-Based Alzheimer's Detection App

### 6.1.3 User engagement:

Healthcare, interpretable concerns Main issue with deep learning is ensuing it is interpretable, so we can build trust in the machine learning model among healthcare professionals, patients and regulatory boddies. Essential for clinicials to comprehend and trust the model so they can make recommendations about the diagnosis and treatmentplan and management. especially since AD is a progressive disease, there are various stages and no set treatment plan.

The demographic that is more suseptible to AD being older population do not have the same relationship with smartphone useage as younger generations. Even if they are confident with technology, aging and neurodegeneration can impact a persons confidence to use technology. Ap would need to be targeted at them; hence, that is why we have gone away from a "gameified" app and more focused on running in the background, set and forget. Given the right permission is given, automatic alerts are sent to doctors, who may then send a message to the person.

## 6.2 Topics beyond the scope

The Intelligent Systems course (34366) at DTU provided a comprehensive overview of various topics, ranging from machine learning fundamentals to advanced applications in IoT, smart cities, and healthcare. While this breadth was instrumental in shaping our understanding, certain elements were either not directly implemented in this project or intentionally excluded due to scope limitations.

For instance, while IoT integration was touched upon in the context of smart speakers, broader applications, such as data management in smart cities or advanced wireless communication protocols, were not explored in depth.
Concepts like intelligent transport systems and industrial automation, though fascinating, had no direct relevance to our project's focus on Alzheimer's detection through speech. However, ideas from these domains—such as distributed system design and resource optimization—could inspire innovative approaches to handling large-scale speech data in the future.

Additionally, topics like fiber-optic communication and smart grid technologies, while central to other intelligent systems, were not applicable to this project's health-centric goals. Instead, our efforts centered on understanding user needs, ensuring data privacy, and developing a user-friendly application tailored to healthcare scenarios.

Ultimately, this project reflects a focused application of the course's teachings, prioritizing depth over breadth in areas most relevant to Alzheimer's detection. However, the excluded elements highlight opportunities for future exploration, ensuring that the knowledge gained from this course can continue to inform and enhance the system as it evolves.

# 7. Conclusion

This report outlines the development and implementation of an AI-based system for the early detection of Alzheimer's Disease (AD) through speech analysis. By integrating state-of-the-art machine learning methodologies, robust preprocessing techniques, and innovative system architecture, the proposed solution addresses the growing need for scalable, non-invasive, and cost-effective diagnostic tools. The system's hybrid architecture, combining edge and cloud computing, ensures both real-time functionality and long-term scalability, while leveraging advancements in IoT devices like smart speakers enhances accessibility and usability.

A key strength of this project lies in its alignment with established medical benchmarks such as ADReSS and ADReSSo, which improve the reliability and clinical relevance of the proposed approach. Despite these advantages, the report identifies several challenges, including data scarcity, privacy concerns, and user engagement barriers, particularly for older populations. These limitations underscore the importance of adopting collaborative approaches, rigorous adherence to data protection regulations, and user-centered design principles to enhance system adoption and effectiveness.

The proposed three-week implementation plan demonstrates the feasibility of developing a functional prototype within a constrained timeline. By targeting both healthcare professionals and at-risk individuals, the business model ensures clinical relevance and widespread adoption.

Although certain topics from the course, such as smart grid applications or intelligent transport systems, were deemed outside the scope of this report, their exclusion allowed for a focused exploration of AI-based Alzheimer's detection. Future research may explore how these technologies can complement the proposed solution, such as integrating environmental sensors or expanding the system for other neurodegenerative conditions.

This project represents a significant step toward leveraging AI and IoT technologies for early Alzheimer's detection. While challenges remain, the potential impact on global health outcomes, particularly in improving early intervention and reducing healthcare burdens, highlights the transformative possibilities of this approach. With continued refinement, collaboration, and ethical considerations, the proposed system can contribute meaningfully to addressing the growing burden of Alzheimer's Disease.

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