LLM-Assisted Early Detection of Alzheimer's Disease Using LoRA

A SEMINAR REPORT SUBMITTED

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE AWARD OF DEGREE OF

BACHELOR OF ENGINEERING
In
CSE (AI/ML)

SUBMITTED BY
Manpreet Singh
2023A6R018

SUBMITTED TO

Computer Science Department

Model Institute of Engineering and Technology (Autonomous)

Jammu, India

2025

CANDIDATES' DECLARATION

I, **Manpreet Singh, 2023A6R018,** hereby declare that the work which is being presented in the seminar report entitled, "**LLM-Assisted Early Detection of Alzheimer's Disease Using LoRA**" in partial fulfillment of requirement for the award of degree of B.E. (CSE (AI/ML)) and submitted in the Computer Science Department, Model Institute of Engineering and Technology (Autonomous), Jammu is an authentic record of my own work carried by me. The matter presented in this seminar report has not been submitted in this or any other University / Institute for the award of B.E. Degree.

Signature of the Student *Dated*: 20/12/2025

Manpreet Singh

2023A6R018

ACKNOWLEDGEMENTS

Seminar work is an important aspect in the field of engineering, where contribution is made by many persons and organizations. The present shape of this work has come forth after contributions from different spheres.

We would like to express our sincere gratitude to the Model Institute of Engineering and Technology (Autonomous), Jammu for providing us with the opportunity to work on this seminar as part of our academic curriculum. This Seminar has been a valuable learning experience, and we are grateful for the guidance and support we received throughout its duration.

We extend our heartfelt thanks to **Prof. (Dr.) Ankur Gupta** (Director MIET), **Dr. Navin Mani Upadhyay** (HOD, CSE) and **Seminar Coordinator** for their continuous encouragement and mentorship. Their insights and guidance have been invaluable in shaping my understanding and approach.

We are also thankful to the faculty members who supported us and provided valuable inputs. Their expertise and dedication have been instrumental in my professional development.

Furthermore, we would like to acknowledge the support of our parents, whose unwavering encouragement and support have been a constant source of motivation for us.

Lastly, we are grateful to our peers and colleagues for their collaboration and camaraderie throughout this journey. Their teamwork and camaraderie have made this experience truly enriching.

At the end thanks to the Almighty for making this academic endeavor possible …………

Manpreet Singh

2023A6R018

ABSTRACT

Alzheimer’s disease is a progressive neurodegenerative disorder that affects millions of people worldwide and is often diagnosed at later stages, limiting treatment effectiveness. Early detection remains a critical challenge due to the subtle and complex linguistic, cognitive, and behavioral markers that appear in patient communication. Recent advances in Large Language Models (LLMs) have shown promising potential in analyzing unstructured medical text, patient interviews, and clinical notes. However, training and fine-tuning these models for specialized healthcare applications require extensive computational resources, which poses a barrier for practical deployment. To address this challenge, this seminar proposes an efficient approach to domain-specific adaptation of LLMs using Low-Rank Adaptation (LoRA). By fine-tuning lightweight adapters instead of retraining entire models, LoRA enables resource-efficient specialization of LLMs for Alzheimer’s detection tasks. The study will involve a comprehensive literature review, implementation of a prototype using open-source LLMs, and evaluation of their effectiveness in identifying early-stage Alzheimer’s indicators.

Contents

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS USED

ANN	Artificial Neural Network
BERT	Bidirectional Encoder Representations from Transformers
EDA	Exploratory Data Analysis
EHR	Electronic Health Records
GPT	Generative Pre-trained Transformer
ICLR	International Conference on Learning Representations
LoRA	Low-Rank Adaptation
LSTM	Long Short-Term Memory
MRI	Magnetic Resonance Imaging
PET	Positron Emission Tomography
SDG	Sustainable Development Goal

Chapter 1

INTRODUCTION

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that affects millions of individuals worldwide, leading to memory loss, cognitive decline, and impaired daily functioning. Despite extensive medical research, the absence of early and reliable detection methods remains a critical barrier to effective intervention. Early diagnosis is vital, as it can enable timely medical care, lifestyle adjustments, and participation in clinical trials that may slow the progression of the disease.

The intersection of AI, machine learning, and healthcare presents a promising frontier where computational methods can assist in identifying early biomarkers of Alzheimer's from speech, text, and clinical notes. By integrating LLMs with LoRA, this research aims to explore scalable, accurate, and accessible tools for the early detection of Alzheimer's disease, contributing to both the medical domain and the broader scope of AI-driven healthcare innovations.

Motivation behind choosing this topic:

1. **Rising Global Burden of Alzheimer's Disease:**
   The increasing prevalence of Alzheimer's Disease due to aging populations presents a critical healthcare challenge worldwide. There is an urgent need for early diagnostic tools that can assist clinicians in identifying the disease at its initial stages, where intervention is most effective.
2. **Potential of LLMs and LoRA in Healthcare AI:**
   Large Language Models have shown exceptional performance in analyzing complex language patterns, which are often affected in early Alzheimer's patients. The use of LoRA enables efficient fine-tuning of these large models, making them practical for real-world healthcare applications without requiring extensive computational resources.

3. **Contribution to Accessible and Sustainable Healthcare Solutions:**
   By leveraging AI-driven, non-invasive, and cost-effective diagnostic approaches, this work aligns with the goal of making healthcare more accessible, especially in resource-constrained environments. The proposed approach supports sustainable medical innovation while addressing a real-world societal problem.

1.1 Significance of the Topic

The significance of this research lies in its focus on addressing one of the most critical challenges in modern healthcare—the early detection of Alzheimer's Disease. With the increasing prevalence of neurodegenerative disorders and the limitations of conventional diagnostic methods, there is a growing need for innovative, efficient, and accessible solutions. By integrating Large Language Models with Low-Rank Adaptation (LoRA), this study highlights a novel approach that combines medical intelligence with computational efficiency. The proposed framework not only enhances diagnostic accuracy but also promotes scalable and sustainable healthcare practices, making it highly relevant in today's data-driven medical landscape.

Critical Need for Early Detection of Alzheimer's Disease

Alzheimer's Disease develops gradually, with early-stage symptoms often going unnoticed or misdiagnosed. Detecting the disease at an early stage is crucial for initiating timely treatment, slowing cognitive decline, and improving the quality of life for patients and caregivers. This topic directly addresses the need for reliable early diagnostic methods that can identify subtle cognitive and linguistic changes before severe symptoms appear.

Application of Large Language Models in Medical Diagnostics

Large Language Models have demonstrated exceptional capability in understanding and analyzing human language patterns. Since language impairment is one of the earliest indicators of Alzheimer's Disease, the use of LLMs provides a powerful and innovative approach for detecting cognitive abnormalities. This enhances the role of artificial intelligence as an intelligent decision-support tool in modern healthcare systems.

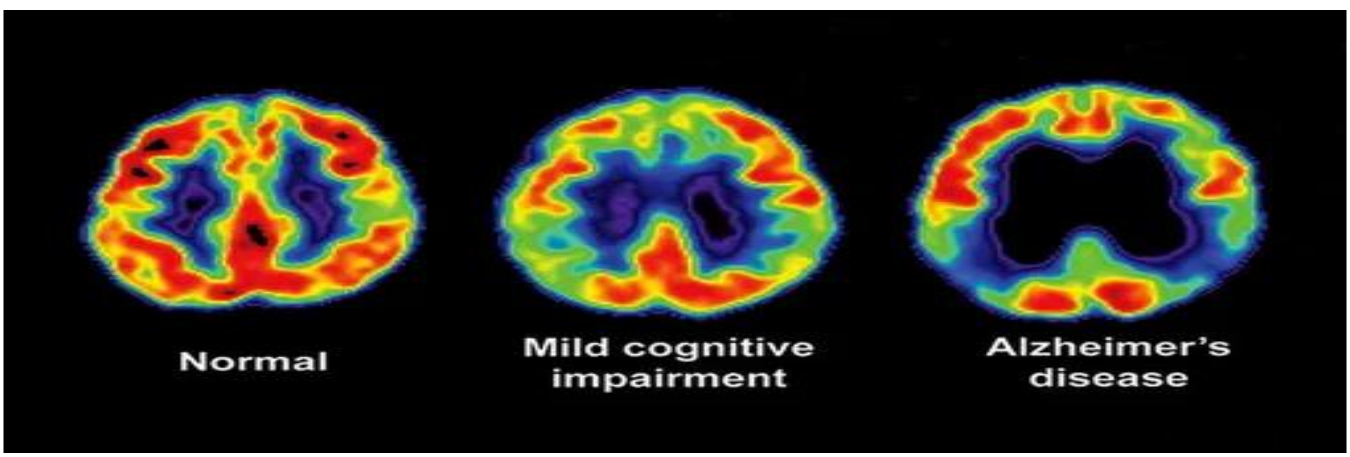

Figure 1.1: Showing difference in apparence of a normal brain and an Alzheimer affected brain.

Efficiency and Practicality Through LoRA-Based Fine-Tuning

Fine-tuning large-scale language models traditionally requires significant computational resources, limiting their real-world applicability. The use of Low-Rank Adaptation (LoRA) enables efficient fine-tuning with reduced memory and computational requirements, making advanced AI models feasible for clinical and research environments without high infrastructure costs.

Non-Invasive, Cost-Effective, and Scalable Healthcare Solution

Unlike conventional diagnostic methods that rely on expensive neuroimaging or invasive biomarker testing, language-based AI analysis is non-invasive and economical. This approach can be easily scaled to screen large populations, making it suitable for both urban healthcare centers and remote or resource-limited regions.

Contribution to Sustainable and Equitable Healthcare Systems

By minimizing resource consumption and improving diagnostic efficiency, this research supports the development of sustainable healthcare solutions. The proposed system helps reduce the burden on healthcare professionals while promoting equitable access to early diagnostic support, aligning technological advancement with long-term societal and environmental sustainability.

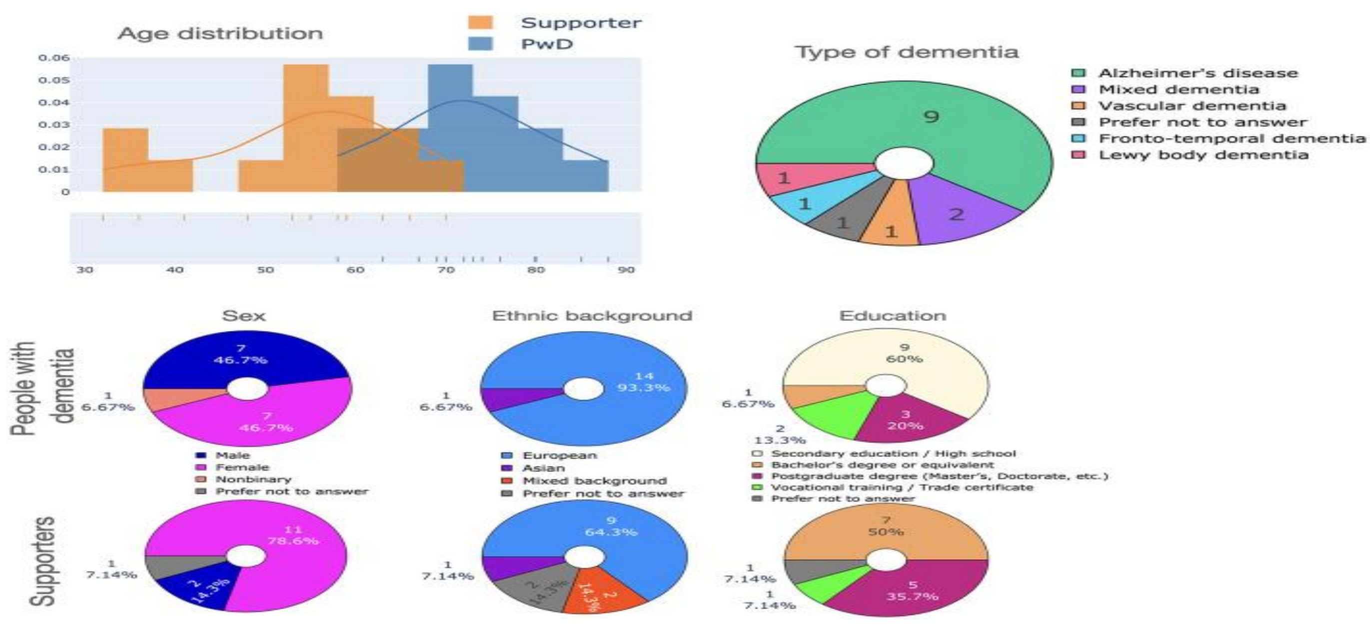

Figure 1.2: Demographic data Top left: age distribution for people with dementia (PwD) and supporters. Top right: types of dementia. Bottom row: sex, ethnic background, and education for people with dementia and supporters.

1.2 Problem Statement and Relevance to SDG

Alzheimer's Disease is one of the leading causes of dementia worldwide and presents a growing challenge for healthcare systems due to its progressive nature and lack of a definitive cure. A major problem in managing Alzheimer's Disease is the difficulty in detecting it at an early stage. Current diagnostic methods largely depend on clinical evaluations, neuroimaging techniques such as MRI and PET scans, and biochemical biomarkers, which are often expensive, invasive, time-consuming, and inaccessible to a large portion of the global population. As a result, many patients are diagnosed only after significant cognitive decline has already occurred, limiting the effectiveness of available treatments and interventions.

In addition to medical challenges, the rising number of Alzheimer's patients places a significant economic and social burden on families, caregivers, and healthcare infrastructures. The shortage of specialized neurologists, especially in developing and rural regions, further worsens the problem by delaying diagnosis and treatment. These limitations highlight the urgent need for an intelligent, scalable, and cost-effective diagnostic support system that can assist healthcare professionals in identifying early signs of the disease.

The proposed LLM-assisted early detection system using LoRA addresses this problem by leveraging language-based analysis to identify subtle cognitive impairments in patients. By fine-tuning large language models efficiently, the system offers a non-invasive, accessible, and resource-efficient approach that can be integrated into existing healthcare frameworks. This method enables early screening, reduces dependency on costly diagnostic procedures, and supports timely clinical decision-making.

From a sustainability perspective, this research aligns closely with the United Nations Sustainable Development Goals (SDGs), particularly SDG 3: Good Health and Well-Being. The proposed solution contributes to improving healthcare quality by promoting early disease detection, preventive care, and reduced mortality associated with neurodegenerative disorders. Furthermore, by emphasizing affordability, accessibility, and efficient use of computational resources, the study also supports SDG 9: Industry, Innovation, and Infrastructure and SDG 10: Reduced Inequalities, ensuring that advanced healthcare technologies can benefit diverse populations across different socio-economic backgrounds.

1.3 Importance in Sustainable Solutions for Real-World Challenges

The growing prevalence of Alzheimer's Disease presents a significant real-world challenge that extends beyond healthcare, affecting social structures, economic stability, and long-term sustainability. Addressing this challenge requires solutions that are not only clinically effective but also economically viable, environmentally responsible, and socially inclusive. The proposed LLM-assisted early detection framework using LoRA offers a sustainable approach by combining technological innovation with practical applicability.

One of the key aspects of sustainability in this research is the emphasis on resource efficiency. Traditional diagnostic methods rely on high-cost medical equipment, specialized facilities, and extensive human expertise, which increases energy consumption and healthcare expenditure. In contrast, the proposed AI-driven approach minimizes reliance on physical infrastructure by utilizing digital language-based assessments, thereby reducing operational costs and resource utilization.

The use of LoRA-based fine-tuning further enhances sustainability by significantly lowering computational and energy requirements. Instead of retraining entire large language models, LoRA enables selective parameter updates, making the system lightweight and suitable for deployment even in low-resource environments. This ensures that advanced AI solutions can be adopted without contributing to excessive carbon footprints or infrastructure strain.

From a societal perspective, the proposed system supports inclusive and equitable healthcare by improving access to early diagnostic tools in underserved and remote regions. Early detection helps patients maintain independence for longer periods, reduces caregiver burden, and improves overall quality of life. This contributes to long-term social sustainability by strengthening community health outcomes and reducing healthcare inequalities.

Overall, this research demonstrates how artificial intelligence can be leveraged to solve real-world healthcare challenges in a sustainable manner. By integrating efficiency, scalability, and accessibility, the proposed solution aligns technological advancement with long-term economic, social, and environmental sustainability, making it a valuable contribution to future healthcare systems.

1.4 Summary

This chapter introduced the research topic *"LLM-Assisted Early Detection of Alzheimer's Disease Using LoRA"* by highlighting its significance, underlying problem, and relevance to sustainable healthcare solutions. It discussed the growing challenges associated with early Alzheimer's diagnosis and emphasized the role of advanced AI techniques in addressing these limitations. The chapter also established the alignment of the proposed approach with global sustainability goals, particularly in promoting accessible, efficient, and equitable healthcare. Overall, this chapter lays a strong foundation for the subsequent chapters by clearly defining the motivation and importance of the study.

Chapter 2

LITERATURE REVIEW

The literature review provides a comprehensive overview of existing research related to the early detection of Alzheimer's Disease using artificial intelligence, machine learning, and natural language processing techniques. It examines prior studies that focus on cognitive assessment, speech and language analysis, and the application of deep learning models in healthcare diagnostics. Special emphasis is placed on recent advancements in Large Language Models and parameter-efficient fine-tuning methods such as Low-Rank Adaptation (LoRA). By analyzing current methodologies, findings, and limitations, this chapter establishes the research context and identifies gaps that motivate the proposed LLM-assisted approach for early Alzheimer's detection.

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was adopted to ensure a transparent, unbiased, and reproducible methodology for selecting research related to Alzheimer's disease detection, large language models (LLMs), and parameter-efficient fine-tuning approaches such as LoRA.

During the identification phase, a total of 46 research records were retrieved from reputable academic databases including IEEE Xplore, Scopus, ACM Digital Library, SpringerLink, and Google Scholar using keywords such as Alzheimer's detection, LLM-based medical analysis, LoRA fine-tuning, dementia speech analysis, clinical NLP, and neurodegenerative disease modeling.

In the screening phase, 28 studies remained after removing duplicates and filtering based on titles and abstracts for relevance to Alzheimer's diagnosis, cognitive impairment assessment, speech or text-based biomarkers, and transformer or LLM-centered medical AI systems.

During the eligibility phase, 15 full-text articles underwent detailed review to evaluate methodological rigor, dataset suitability (e.g., ADReSS, DementiaBank, ADNI), use of transformer architectures, application of LoRA or other PEFT methods, and overall relevance to early-stage Alzheimer's detection.

Finally, in the inclusion phase, 10 high-quality studies met all criteria and were selected for qualitative synthesis. These studies collectively explored advancements in LLM-assisted cognitive assessment, speech and linguistic biomarker modeling, LoRA-based fine-tuning for domain adaptation, multimodal fusion approaches, and evaluation metrics for clinical diagnosis. They also identified persisting challenges such as limited domain-specific datasets, variability in speech patterns, ethical and clinical reliability concerns, privacy restrictions, and the need for more robust fine-tuned LLMs that can support early medical decision-making.

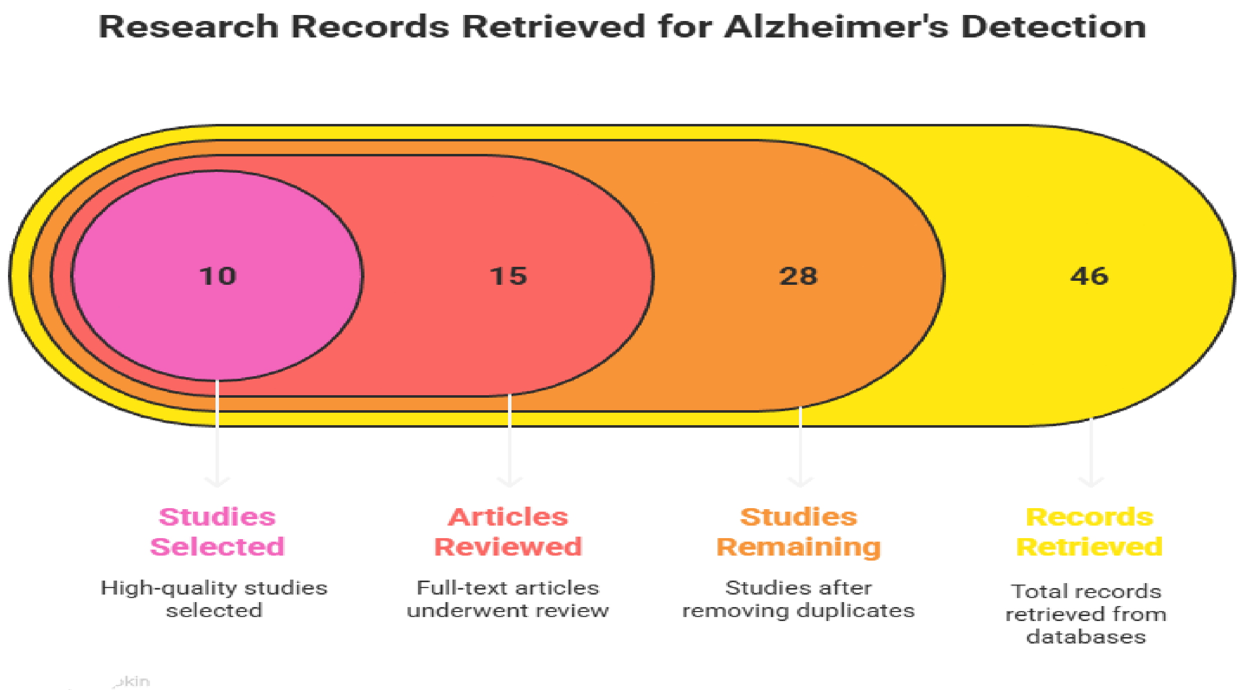

Figure 2.1: Showing PRISMA technique

2.1 Key Findings and Recent Advancements

Recent research in the field of Alzheimer’s Disease detection has increasingly focused on the application of artificial intelligence and machine learning techniques to improve diagnostic accuracy and enable early-stage identification. Traditional approaches relied primarily on neuroimaging data, clinical cognitive tests, and biochemical biomarkers. While effective, these methods are often expensive, invasive, and not suitable for large-scale screening. As a result, researchers have explored alternative data sources such as speech, text, and behavioral patterns, which have shown strong correlations with early cognitive decline.

One of the key findings in recent studies is that language impairment is an early indicator of Alzheimer’s Disease. Changes in vocabulary usage, sentence structure, coherence, and speech fluency have been consistently observed in individuals with mild cognitive impairment and early-stage Alzheimer's. Natural Language Processing (NLP) techniques have been widely adopted to extract linguistic features such as lexical diversity, syntactic complexity, semantic coherence, and pause duration. Machine learning models trained on these features have demonstrated promising results in distinguishing Alzheimer's patients from healthy individuals.

With the advancement of deep learning, transformer-based architectures have significantly improved language modeling capabilities. Models such as BERT, GPT, and other large-scale language models have shown superior performance in capturing contextual and semantic information from textual data. Recent studies have reported improved classification accuracy when using pre-trained language models for Alzheimer's detection tasks compared to traditional machine learning classifiers. These models are capable of learning subtle language patterns that are difficult to identify using handcrafted features alone.

Another major advancement is the introduction of Large Language Models (LLMs) in clinical decision support systems. LLMs enable end-to-end learning by directly processing raw text or transcribed speech data, reducing the need for extensive feature engineering. Research has demonstrated that fine-tuned LLMs can effectively analyze patient narratives, clinical notes, and conversational responses to detect early cognitive impairment with high reliability.

However, the large size of these models introduces challenges related to computational cost and deployment feasibility. To address this, parameter-efficient fine-tuning techniques such as Low-Rank Adaptation (LoRA) have gained attention. LoRA allows only a small subset of model parameters to be trained while keeping the original model weights frozen. Recent studies have shown that LoRA-based fine-tuning achieves performance comparable to full model fine-tuning while significantly reducing memory usage, training time, and energy consumption.

In addition, advancements in multimodal learning have enhanced Alzheimer's detection by combining linguistic data with acoustic, behavioral, and demographic features. Integrating speech patterns, text analysis, and cognitive scores has resulted in more robust and accurate prediction models. Cloud-based and edge-AI implementations have further improved the scalability of such systems, enabling real-time analysis and remote monitoring.

Overall, the literature indicates a clear shift toward AI-driven, language-based diagnostic approaches supported by efficient fine-tuning strategies. These advancements highlight the growing potential of LLM-assisted systems to transform early Alzheimer's detection into a scalable, accurate, and accessible healthcare solution.

2.2 Gaps, Challenges, and Limitations in Current Research

Despite significant advancements in artificial intelligence–based approaches for Alzheimer's Disease detection, existing research still faces several gaps, challenges, and limitations that hinder real-world deployment and large-scale adoption. One of the primary gaps in current studies is the lack of reliable early-stage detection models. Many existing systems perform well only when the disease has progressed to moderate or severe stages, while accurately identifying subtle cognitive changes during the early or preclinical phase remains a major challenge. A critical limitation observed in the literature is the dependency on small and homogeneous datasets. Most Alzheimer's detection studies rely on publicly available datasets that have limited sample sizes and lack demographic diversity. This restricts the generalizability of models and increases the risk of bias, making it difficult to apply these systems across different populations, languages, and cultural contexts. Furthermore, data imbalance between healthy subjects and Alzheimer's patients often leads to skewed model performance.

Another major challenge is the high computational cost of large language models. While LLMs have demonstrated superior performance in language understanding tasks, their deployment in healthcare settings is limited by memory requirements, energy consumption, and the need for high-performance hardware. Many existing studies either ignore these constraints or rely on cloud-based infrastructure, which raises concerns related to cost, latency, and data privacy.

The lack of interpretability and explainability is another significant limitation. Many deep learning and transformer-based models function as black-box systems, providing predictions without clear explanations. In medical applications, this lack of transparency reduces clinician trust and limits clinical adoption. Healthcare professionals require understandable reasoning behind AI-driven decisions, especially in sensitive diagnostic scenarios such as Alzheimer's detection. Additionally, privacy and ethical concerns pose challenges in the adoption of AI-based diagnostic tools. Patient data, particularly speech recordings and clinical notes, contain sensitive information. Existing research often lacks robust mechanisms for ensuring data security, anonymization, and compliance with healthcare regulations. This creates barriers to real-world implementation and large-scale data sharing.

From a methodological perspective, many studies focus on model accuracy while neglecting sustainability and deployment feasibility. Few works consider energy-efficient training, resource optimization, or long-term maintenance of AI systems. This gap highlights the need for approaches that balance performance with computational efficiency and environmental responsibility. Finally, there is limited research on the integration of parameter-efficient fine-tuning techniques such as LoRA in clinical Alzheimer's detection systems. While LoRA has shown promise in reducing training costs, its application in healthcare-specific LLM-based diagnostic frameworks remains underexplored. Addressing these gaps is essential to develop scalable, interpretable, and sustainable AI solutions for early Alzheimer's Disease detection.

Table 2.1: Literature Review Table

S.No.	Author(s) & Year	Model/Technique Used	Key Contribution	Dataset/Domain	Identified Limitations	Future Scope
1	Han et al., 2024	PEFT methods incl. LoRA	Taxonomy of PEFT methods	NLP benchmarks	No medical evaluation	Apply PEFT to clinical datasets
2	Alsubaie, 2024	DL on MRI/PET	Review of DL pipelines	ADNI, OASIS	No language features	Integrate LLM speech/notes
3	Ali et al., 2024	CNNs for MRI	MRI diagnostic pipeline	ADNI MRI	Only imaging	Add LLM reasoning
4	Bang et al., 2024	ChatGPT for speech	Zero-shot LLM on AD speech	ADReSS	Inconsistent reliability	LoRA fine-tuning
5	Chen et al., 2021	Speech DL models	Spontaneous speech detection	ADReSS	No transformers	Use LLMs for semantics
6	Ye et al., 2023–24	mLoRA	Efficient multi-adapter LoRA	NLP tasks	Not medical tested	Use in hospitals
7	Yang et al., 2022	DL speech models	Review of speech AD models	Pitt, ADReSS	No LLMs	Semantic LLM modeling
8	Singhal et al., 2023	Med-PaLM	LLMs with clinical reasoning	Medical QA	Not disease-specific	LoRA tuning for Alzheimer

9	Hu et al., 2021	LoRA	PEFT method introduction	NLP tasks	Not medical	Alzheimer domain tuning
10	Yang et al., 2020–21	Survey on speech markers	Linguistic biomarkers	DementiaBank	Classical ML	Use transformers/LLMs

Table 1 shows a structured summary of the key research studies relevant to the topic "LLM Assisted Early Detection of Alzheimer's Disease Using LoRA." The table organizes ten selected papers in descending chronological order and provides a comparative overview across six analytical dimensions: author(s) and publication year, model or technique used, key contribution, dataset or domain, identified limitations, and future scope. This structured representation helps highlight how recent advancements in parameter-efficient fine-tuning (such as LoRA), large language models, and deep learning architectures have contributed to Alzheimer's detection research across speech, text, and neuroimaging modalities.

The table also emphasizes gaps in current literature—including dataset scarcity, limited clinical validation, inconsistent LLM performance, and lack of domain-specific fine-tuning—which collectively justify the need for further exploration of LoRA-based LLM specialization for early stage Alzheimer's prediction. Overall, Table 1 provides a clear foundation for understanding current progress, methodological trends, and the evolving research landscape in Alzheimer's focused LLM and LoRA applications.

2.3 Summary of Literature and Context Setting

The literature reviewed in this chapter highlights the growing role of artificial intelligence and natural language processing in the early detection of Alzheimer's Disease. Previous studies have demonstrated that linguistic and cognitive changes serve as reliable indicators of early-stage Alzheimer's, and the use of machine learning and deep learning models has significantly improved diagnostic performance. Recent advancements in transformer-based architectures and Large Language Models have further enhanced the ability to capture complex language patterns associated with cognitive decline.

However, the review also reveals several limitations in existing research, including reliance on limited datasets, high computational costs, lack of interpretability, and challenges related to scalability and sustainability. While parameter-efficient fine-tuning methods such as LoRA offer promising solutions to these issues, their application in healthcare-focused LLM-based diagnostic systems remains relatively underexplored.

Based on these findings, the current research is positioned to address the identified gaps by proposing an LLM-assisted early detection framework that leverages LoRA for efficient and scalable model adaptation. This context establishes a clear justification for the proposed approach and provides a strong foundation for the methodology and system design discussed in the subsequent chapters.

Chapter 3

UNDERSTANDING TECHNICAL APPROACHES

3.1 Overview of Relevant Technical Approaches

The early detection of Alzheimer's Disease using artificial intelligence relies on a combination of advanced computational techniques drawn from machine learning, deep learning, and natural language processing. These approaches aim to analyze subtle cognitive and linguistic patterns that may not be easily identifiable through traditional diagnostic methods. The proposed framework integrates multiple technical components to achieve accurate, efficient, and scalable detection. One of the primary technical approaches involves Natural Language Processing (NLP), which focuses on analyzing patient speech transcripts, written responses, or conversational data. NLP techniques are used to examine linguistic features such as vocabulary richness, grammatical structure, semantic coherence, and discourse patterns. These features have been shown to reflect early cognitive decline in individuals with Alzheimer's Disease.

Another important approach is the use of machine learning and deep learning models for classification and prediction tasks. Traditional machine learning algorithms such as Support Vector Machines and Random Forests have been widely used in earlier studies. However, recent research has shifted toward deep learning models, particularly transformer-based architectures, due to their superior ability to capture contextual relationships in language data.

Large Language Models (LLMs) represent a significant advancement in this domain. Pre-trained on vast amounts of textual data, LLMs possess a strong understanding of language semantics and structure. When fine-tuned on domain-specific medical data, these models can effectively detect linguistic abnormalities associated with early-stage Alzheimer's Disease. Their ability to process raw text data reduces the need for extensive feature engineering, simplifying the diagnostic pipeline.

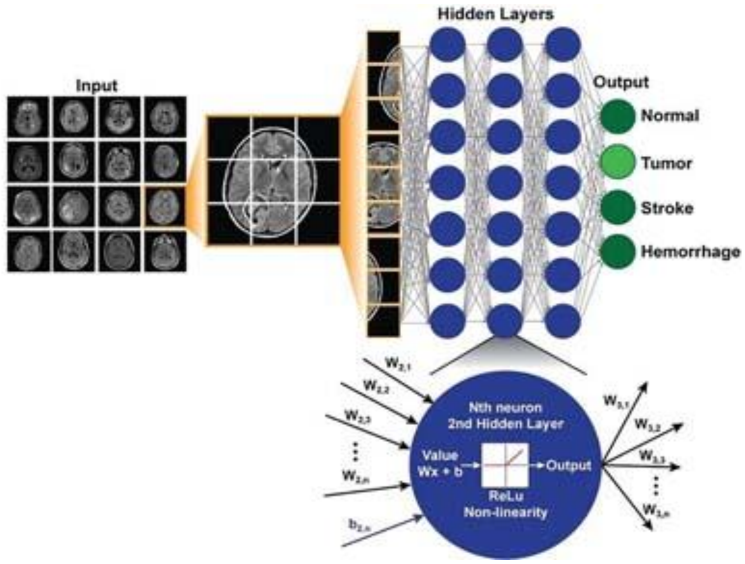

Figure 3.1: showing a CNN model for image classification of brain.

To address the challenges associated with the large size and computational demands of LLMs, parameter-efficient fine-tuning techniques are employed. Among these, Low-Rank Adaptation (LoRA) has emerged as an effective method that allows fine-tuning of large models by introducing low-rank matrices into specific layers. This approach significantly reduces training cost, memory usage, and energy consumption while maintaining high performance.

Additionally, the integration of cloud-based and edge computing frameworks has been explored to support real-time analysis and remote healthcare monitoring. These deployment strategies enhance system scalability and accessibility, enabling AI-assisted diagnostic tools to be used in diverse clinical settings.

Overall, the technical approaches discussed in this section form a comprehensive foundation for building an intelligent, efficient, and sustainable system for early Alzheimer's Disease detection. They collectively address the challenges of accuracy, scalability, and real-world applicability in modern healthcare environments.

3.2 Key Techniques and Methodologies

The proposed LLM-assisted early detection framework for Alzheimer's Disease is built upon a set of key techniques and methodologies that collectively enable accurate, efficient, and scalable diagnostic support. These techniques span data processing, model selection, fine-tuning strategies, and evaluation mechanisms, ensuring a robust and practical system design.

A fundamental technique employed in this approach is language-based data acquisition and preprocessing. Patient speech or written text is collected through cognitive assessments, interviews, or conversational prompts. This data undergoes preprocessing steps such as noise removal, text normalization, tokenization, and sentence segmentation. These steps ensure that the input data is structured and suitable for model training and inference.

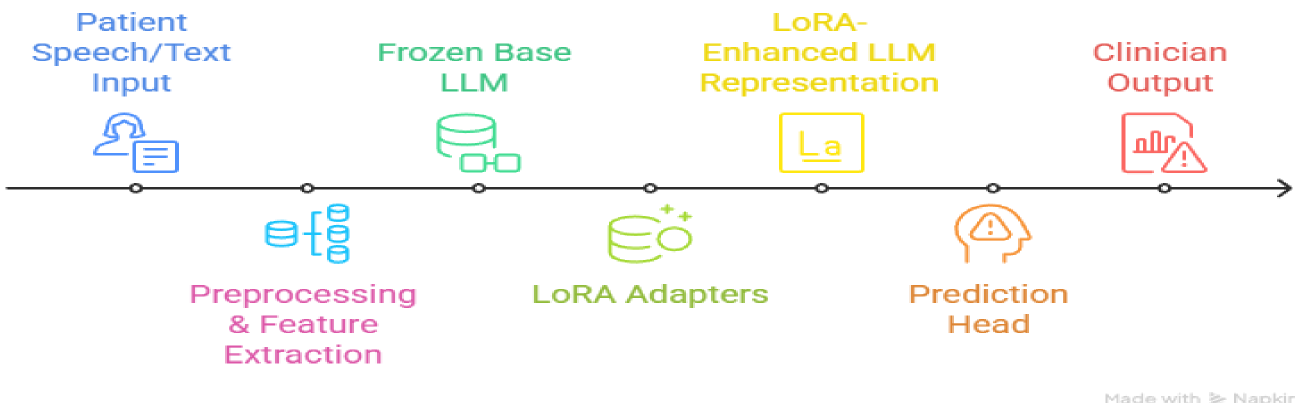

Figure 3.2: showing working of a LLM on textual/voice input

The core methodology revolves around the use of Large Language Models (LLMs) for cognitive analysis. LLMs leverage transformer architectures with self-attention mechanisms to capture contextual relationships within text. Their deep semantic understanding allows them to identify subtle linguistic abnormalities, such as reduced sentence complexity, repetitive phrasing, and semantic incoherence, which are commonly associated with early Alzheimer's Disease.

To adapt these models for the specific healthcare task, fine-tuning is performed using labeled Alzheimer's-related datasets. Instead of updating all model parameters, the framework employs Low-Rank Adaptation (LoRA). LoRA introduces trainable low-rank matrices into selected layers of the LLM, enabling efficient domain adaptation while keeping the majority of the model parameters frozen. This significantly reduces training time, memory consumption, and computational cost, making the approach suitable for real-world deployment. Another important methodology is the incorporation of evaluation and validation techniques to assess model performance. Metrics such as accuracy, precision, recall, F1-score, and confusion matrices are commonly used to evaluate diagnostic reliability. Cross-validation strategies are applied to ensure robustness and prevent overfitting, especially when working with limited medical datasets.

The framework may also integrate ethical and privacy-preserving techniques, including data anonymization and secure model deployment practices, to ensure compliance with healthcare data protection standards. These considerations are essential for building trustworthy and clinically acceptable AI systems.

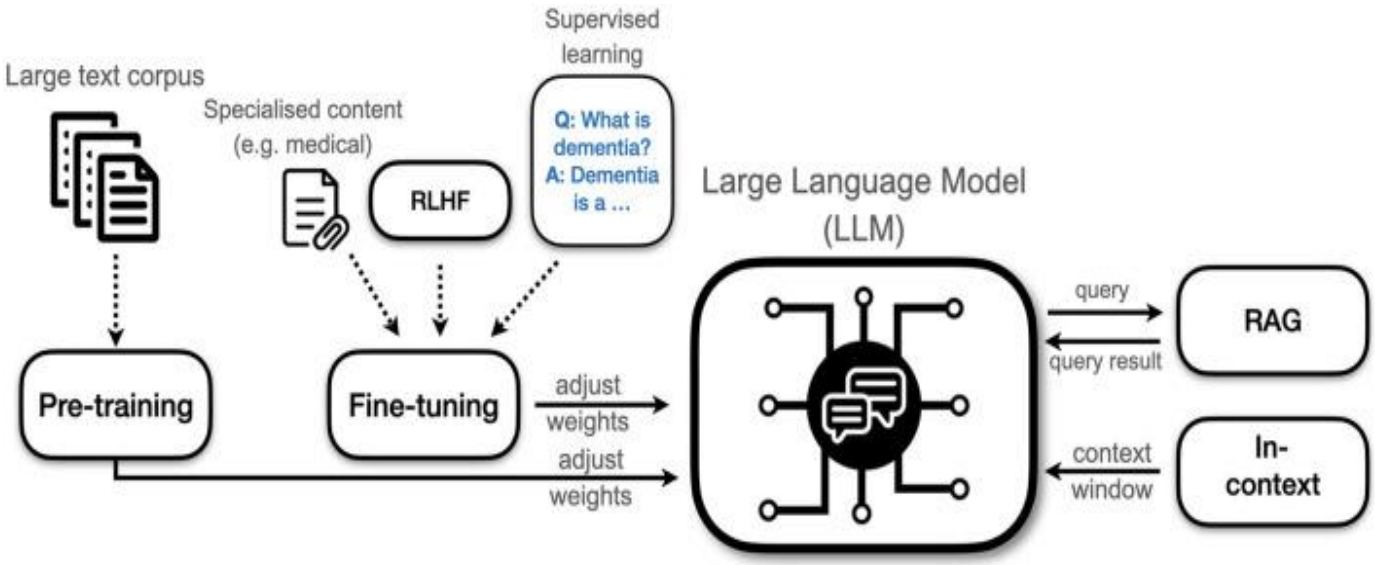

Figure 3.3: showing how a model would work with fine-tuning and RAG

Together, these techniques and methodologies form a comprehensive technical pipeline that balances performance, efficiency, and sustainability. By combining advanced language modeling with resource-efficient fine-tuning, the proposed approach addresses both the technical and practical challenges of early Alzheimer’s Disease detection.

3.3 Summary of Technical Insights

This chapter presented a comprehensive overview of the technical approaches and methodologies relevant to LLM-assisted early detection of Alzheimer’s Disease. It highlighted the role of natural language processing in analyzing linguistic patterns indicative of cognitive decline and emphasized the effectiveness of transformer-based large language models in capturing complex semantic relationships. The use of Low-Rank Adaptation (LoRA) was identified as a key strategy for enabling efficient and scalable fine-tuning of large models without excessive computational overhead. Overall, the technical insights discussed in this chapter establish a strong foundation for designing an accurate, resource-efficient, and sustainable AI-driven diagnostic framework, which will be further elaborated in the subsequent chapters.

Chapter 4

EXISTING PROTOTYPES AND SOLUTIONS

This chapter reviews existing prototypes, systems, and technological solutions developed for the early detection of Alzheimer's Disease using artificial intelligence and machine learning techniques. It focuses on currently available research models, experimental frameworks, and clinical decision-support systems that utilize language, speech, and cognitive data. By analyzing their effectiveness, scalability, and real-world applicability, this chapter provides a comparative perspective and highlights the practical challenges that motivate the proposed LLM-assisted approach.

4.1 Overview of Relevant Prototypes and Models

Over the past decade, numerous prototypes and AI-driven models have been proposed to support the early detection of Alzheimer's Disease, reflecting the growing interest in leveraging computational intelligence for neurological healthcare. Initial research efforts primarily focused on traditional machine learning–based prototypes, where handcrafted features were extracted from patient speech, text, and cognitive test results. These features included measures of lexical diversity, syntactic complexity, speech fluency, and pause duration. Classification models such as Support Vector Machines (SVM), Decision Trees, Random Forests, and Naïve Bayes classifiers were commonly employed. While these approaches demonstrated promising results in controlled environments, their dependence on manual feature engineering limited adaptability and scalability.

As deep learning gained prominence, researchers began developing neural network–based prototypes, particularly using Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) architectures. These models were better suited for sequential data analysis and enabled improved modeling of temporal language patterns. Such prototypes showed enhanced performance over traditional methods, especially in analyzing speech transcripts and narrative responses. However, they often required large labeled datasets and struggled to capture long-range contextual relationships within language.

More recent solutions have adopted transformer-based architectures and Large Language Models (LLMs), which represent a significant advancement in Alzheimer's detection research. Pre-trained models such as BERT and GPT variants have been fine-tuned on medical and cognitive datasets to analyze linguistic coherence, semantic consistency, and discourse-level abnormalities. Several prototypes integrate conversational agents or virtual assessment tools that interact with patients and analyze responses in real time. These systems have demonstrated higher diagnostic accuracy and improved sensitivity to early-stage cognitive decline.

In addition to language-only models, multimodal prototypes have been developed that combine textual data with acoustic features, behavioral indicators, and demographic information. By integrating multiple data sources, these models aim to improve robustness and reduce misclassification. Furthermore, web-based and cloud-enabled platforms have been introduced to facilitate remote cognitive assessment, enabling wider accessibility and continuous monitoring.

Overall, existing prototypes and models demonstrate steady progress toward AI-assisted Alzheimer's detection. However, their complexity, computational demands, and deployment challenges highlight the need for more efficient and scalable approaches—providing the motivation for LLM-assisted frameworks enhanced with parameter-efficient techniques such as LoRA.

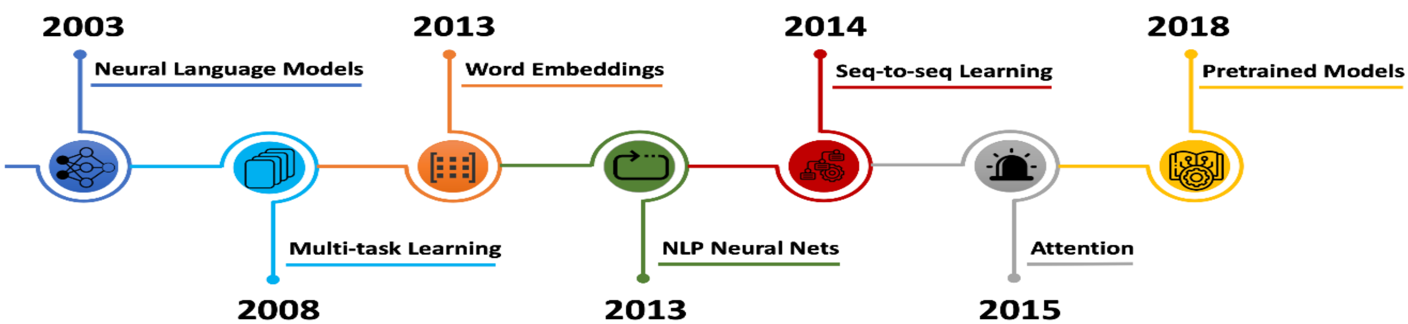

Figure 4.1: Evolution of AI-based models for Alzheimer's Disease detection

4.2 Evaluation of Effectiveness and Scalability

The effectiveness of existing Alzheimer's detection prototypes is generally assessed using performance metrics such as accuracy, precision, recall, F1-score, and sensitivity to early-stage cognitive impairment. Traditional machine learning–based models have shown moderate effectiveness, particularly when applied to well-structured datasets with carefully engineered linguistic features. However, their performance often degrades when exposed to real-world data variations, limiting their reliability in practical healthcare settings.

Deep learning–based prototypes, especially those using recurrent and transformer-based architectures, have demonstrated improved effectiveness by capturing complex linguistic and contextual patterns. Large Language Models (LLMs), in particular, have shown strong capabilities in identifying subtle language irregularities associated with early Alzheimer's Disease. Studies report higher diagnostic accuracy and better generalization compared to earlier models, making LLM-based solutions more promising for clinical support.

Table 4.1: Comparison of Existing Alzheimer's Detection Models

Model Type	**Data Used**	**Key Strengths**	**Limitations**
Traditional ML (SVM, RF)	Handcrafted linguistic features	Simple, interpretable	Low scalability, feature dependency
RNN / LSTM	Speech & text sequences	Temporal pattern learning	High data requirement
Transformer-based Models	Raw text transcripts	Strong contextual understanding	High computational cost
LLM-based Systems	Text / conversational data	High accuracy, minimal feature engineering	Deployment complexity

Despite these improvements, scalability remains a significant challenge. High-performing deep learning models typically require substantial computational resources for training and inference. The large size of LLMs leads to increased memory usage, longer processing times, and higher energy consumption. These factors limit their deployment in resource-constrained environments such as rural healthcare centers or small clinics.

Cloud-based implementations partially address scalability by providing on-demand computing resources; however, they introduce concerns related to latency, cost, data privacy, and dependency on continuous internet connectivity. On the other hand, lightweight or edge-based solutions improve accessibility but often sacrifice model performance. This trade-off between accuracy and efficiency remains a major limitation of existing systems.

Overall, while current prototypes demonstrate strong diagnostic potential, their scalability is constrained by infrastructure requirements and operational costs. These limitations emphasize the importance of adopting efficient fine-tuning strategies, such as LoRA, to maintain effectiveness while enabling practical and sustainable large-scale deployment.

4.3 Analysis of Limitations and Practical Applications

Although existing prototypes for Alzheimer's Disease detection have shown encouraging results, several limitations hinder their widespread adoption in real-world healthcare environments. One of the primary limitations is the computational complexity of advanced AI models, particularly Large Language Models. These models require significant processing power, memory, and energy, making them difficult to deploy in settings with limited technical infrastructure.

Another major limitation is the lack of interpretability and transparency in AI-driven diagnostic systems. Many deep learning models function as black-box systems, providing predictions without clear explanations of the underlying reasoning. In clinical practice, this reduces trust among healthcare professionals and complicates the integration of such systems into medical decision-making processes.

Data-related challenges also persist. Many prototypes are trained on small, controlled, or homogeneous datasets, which limits their ability to generalize across diverse populations, languages, and cultural contexts. Additionally, variations in speech patterns, education levels, and linguistic backgrounds can affect model performance, leading to biased or inconsistent results.

From an ethical and regulatory perspective, privacy and data security concerns present significant barriers. Speech recordings and medical data are highly sensitive, and many existing solutions lack robust mechanisms for secure data handling, anonymization, and compliance with healthcare regulations. These concerns must be addressed to ensure safe and responsible deployment.

Despite these limitations, existing systems demonstrate valuable practical applications. AI-assisted models can serve as early screening tools, helping clinicians identify potential cognitive decline before severe symptoms emerge. They can also support remote monitoring and telemedicine applications, particularly in underserved regions. When used as decision-support systems rather than standalone diagnostic tools, these prototypes have the potential to improve clinical efficiency and patient outcomes.

Overall, the analysis of current limitations highlights the need for efficient, interpretable, and privacy-aware solutions. Incorporating parameter-efficient fine-tuning techniques such as LoRA offers a promising path toward overcoming these challenges and enabling sustainable, real-world deployment of Alzheimer's detection systems.

Chapter 5

REAL-WORLD APPLICATIONS AND IMPACT

This chapter focuses on the practical implications of LLM-assisted early detection of Alzheimer’s Disease using LoRA in real-world settings. It examines how such AI-driven systems can create meaningful impact across healthcare industries and society at large. The chapter also explores the role of this technology in solving real-world challenges and its adaptability across diverse clinical, social, and technological contexts.

5.1 Industry and Societal Impact

The application of LLM-assisted systems for early detection of Alzheimer’s Disease has the potential to significantly transform both the healthcare industry and society as a whole. From an industry perspective, the integration of artificial intelligence into diagnostic workflows enhances the efficiency and accuracy of clinical decision-making. Healthcare providers can leverage AI-based screening tools to support neurologists and clinicians by identifying early signs of cognitive decline, thereby reducing diagnostic delays and improving patient care outcomes.

In the healthcare industry, such systems contribute to cost reduction and operational efficiency. Early detection helps minimize long-term treatment expenses by enabling timely intervention and preventive care. By reducing reliance on expensive diagnostic procedures such as advanced neuroimaging, AI-driven solutions offer a more economical alternative for large-scale screening programs. This is particularly beneficial for hospitals, diagnostic centers, and insurance providers seeking sustainable healthcare models.

From a societal standpoint, early identification of Alzheimer’s Disease has a profound impact on patient quality of life and caregiver well-being. Early diagnosis allows individuals to plan for the future, maintain independence for longer periods, and access appropriate medical and psychological support. It also reduces emotional and financial stress on caregivers and families, who often bear the long-term burden of disease management.

Furthermore, the adoption of efficient AI technologies supports equitable access to healthcare. By enabling remote and language-based assessments, these systems can reach underserved populations and rural communities where specialized neurological services are limited. This contributes to reducing healthcare disparities and promoting inclusive medical support.

Overall, the industry and societal impact of LLM-assisted Alzheimer's detection systems is substantial. By combining technological innovation with healthcare sustainability, these solutions pave the way for improved diagnostic practices, enhanced patient outcomes, and a more resilient healthcare ecosystem.

Table 5.1: Industry-Level Applications of LLM-Assisted Detection

Sector	**Application**
Hospitals	Early cognitive screening support
Diagnostic Centers	Pre-assessment and referral filtering
Telemedicine	Remote cognitive evaluation
Insurance	Risk assessment and preventive planning
Research Institutes	Cognitive pattern analysis

5.2 Application in Real-World Problem Solving

The LLM-assisted early detection framework for Alzheimer's Disease plays a crucial role in addressing several real-world healthcare challenges. One of the primary applications of this technology is in early cognitive screening, where language-based AI systems can analyze patient speech or written responses to identify subtle signs of cognitive decline. This allows healthcare providers to detect potential risks at an early stage, even before noticeable clinical symptoms appear.

Another important application is in remote and telemedicine-based healthcare services. AI-driven diagnostic tools can be integrated into virtual consultation platforms, enabling patients to undergo preliminary cognitive assessments from their homes. This is particularly valuable for elderly individuals, individuals with mobility constraints, and those living in rural or underserved regions. Such applications reduce the need for frequent hospital visits while ensuring continuous cognitive monitoring.

The proposed system also addresses the challenge of limited availability of neurological specialists. By serving as an intelligent decision-support tool, the system assists general practitioners and primary care providers in identifying patients who may require further neurological evaluation. This helps optimize specialist referrals and reduces the diagnostic workload in overcrowded healthcare facilities.

In addition, AI-assisted language analysis can be applied in long-term patient monitoring and disease progression tracking. Regular analysis of patient language patterns over time enables clinicians to observe cognitive changes and adjust treatment strategies accordingly. This proactive approach improves disease management and enhances patient outcomes.

Table 5.2: Mapping of Real-World Problems to AI-Based Solutions

Real-World Challenge	**AI-Based Solution**
Late diagnosis	Early language-based screening
Specialist shortage	AI decision-support
High diagnostic cost	Non-invasive analysis
Rural healthcare gaps	Remote AI assessments

Beyond clinical settings, the framework can be applied in public health initiatives and community screening programs. Large-scale deployment of such systems enables early identification of at-risk populations, supports preventive healthcare strategies, and contributes to better resource planning at the societal level. Overall, the application of LLM-assisted systems demonstrates a practical and scalable solution to real-world challenges associated with Alzheimer's Disease detection and management.

5.3 Integration and Adaptability in Different Contexts

The effectiveness of LLM-assisted early detection systems for Alzheimer's Disease largely depends on their ability to integrate seamlessly into diverse real-world environments and adapt to varying technological, clinical, and social contexts. One of the key strengths of the proposed approach is its flexibility in integration with existing healthcare infrastructures. The system can be incorporated into electronic health record (EHR) platforms, telemedicine applications, and clinical decision-support systems, enabling smooth adoption without disrupting established medical workflows.

From a technological perspective, the use of LoRA-based fine-tuning enhances adaptability by allowing models to be customized for specific datasets, languages, or clinical requirements with minimal computational overhead. This makes the system suitable for deployment across hospitals, clinics, research institutions, and even low-resource healthcare settings. The lightweight nature of LoRA-enabled models also supports edge and cloud-based implementations, ensuring accessibility across different infrastructure levels.

The system is highly adaptable to linguistic and cultural diversity, which is critical in global healthcare applications. By fine-tuning language models on region-specific data, the framework can effectively analyze speech and text in different languages and dialects. This adaptability improves diagnostic accuracy and ensures fair and inclusive healthcare delivery across diverse populations.

In addition, the framework can be tailored to meet regulatory, ethical, and privacy requirements across different regions. Techniques such as data anonymization, secure model deployment, and controlled data access support compliance with healthcare data protection standards. This enhances trust and facilitates broader adoption in clinical environments.

Overall, the integration and adaptability of LLM-assisted systems make them suitable for a wide range of real-world contexts. Their ability to operate across different technological platforms, healthcare settings, and population groups underscores their potential as a sustainable and scalable solution for early Alzheimer's Disease detection.

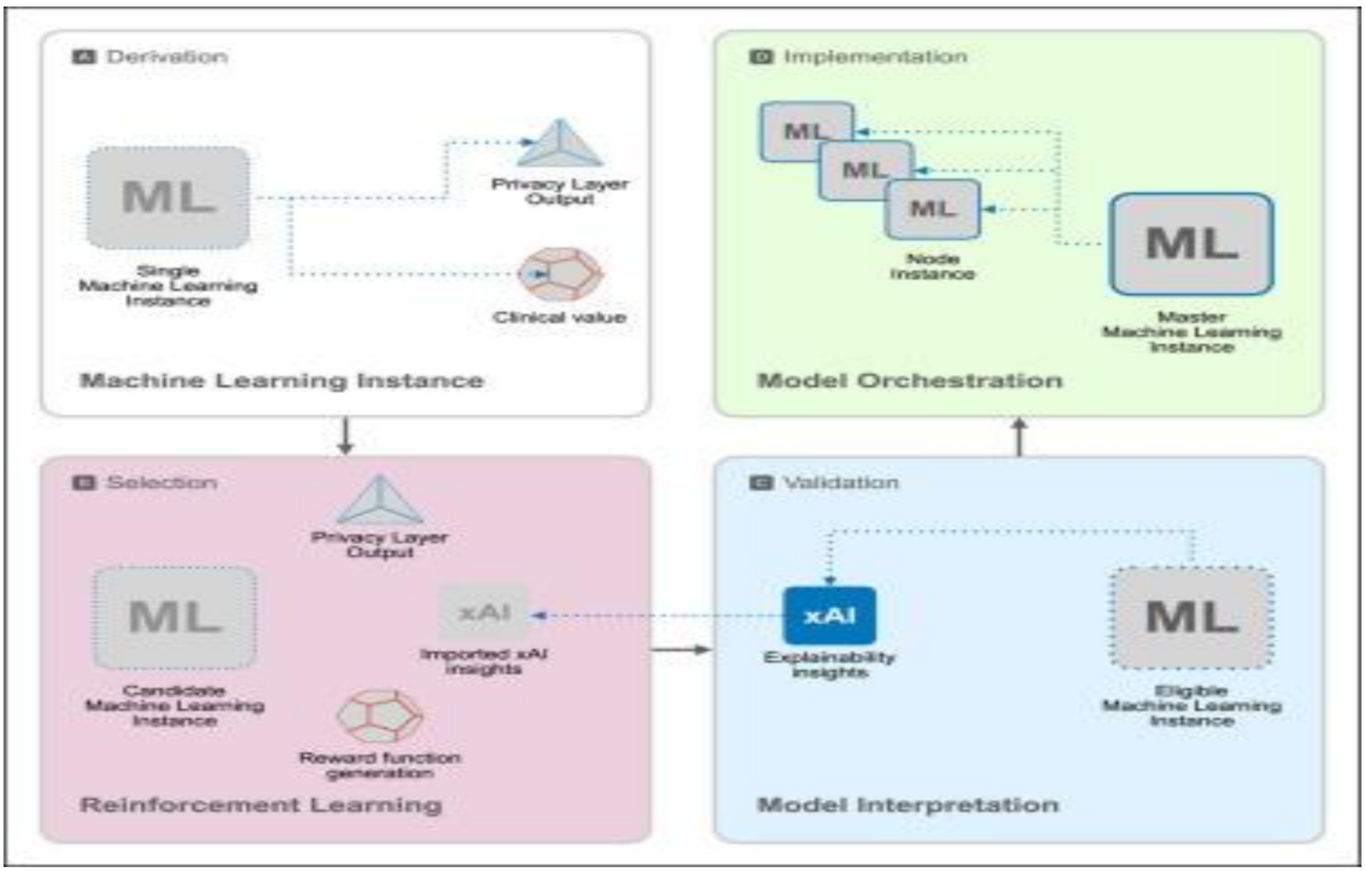

Figure 5.1: Adaptability of LLM-assisted systems across different healthcare contexts

Chapter 6

FUTURE DIRECTIONS AND INNOVATION

This chapter explores the future potential of LLM-assisted early detection systems for Alzheimer's Disease, focusing on emerging technological trends, innovative applications, and long-term sustainability. It highlights how advancements in artificial intelligence, healthcare analytics, and interdisciplinary research can further enhance the effectiveness, scalability, and societal impact of such systems. The chapter also examines how future innovations can contribute to sustainable healthcare development and address evolving real-world challenges.

6.1 Emerging Trends and Future Applications

The field of AI-assisted healthcare is rapidly evolving, and the early detection of Alzheimer's Disease using Large Language Models is expected to benefit significantly from emerging technological trends. One of the most prominent trends is the development of next-generation Large Language Models that exhibit improved contextual understanding, reduced hallucination, and enhanced domain specialization. These models are increasingly being trained with medical and clinical knowledge, enabling more accurate analysis of cognitive and linguistic impairments. Another emerging trend is the integration of multimodal intelligence, where language-based analysis is combined with speech acoustics, facial expressions, handwriting patterns, and behavioral data. Future Alzheimer's detection systems are expected to utilize multimodal LLM frameworks that can process diverse data streams simultaneously, resulting in more robust and reliable predictions. This approach improves early-stage detection by capturing subtle cognitive signals that may not be evident through language analysis alone.

The adoption of personalized and adaptive AI models is also gaining momentum. Future systems may continuously learn from individual patient data over time, allowing for personalized cognitive baselines and more precise detection of deviations. LoRA-based fine-tuning plays a critical role in enabling such personalization without requiring full model retraining, making adaptive healthcare AI both efficient and scalable.

Another significant future application lies in real-time monitoring and preventive healthcare. AI-driven conversational agents and virtual assistants can be deployed for continuous cognitive assessment, providing early warnings and risk scores. These systems can be integrated into smart healthcare platforms, enabling proactive intervention rather than reactive treatment.

Advancements in edge AI and federated learning are expected to further enhance privacy and scalability. By processing sensitive data locally on devices and sharing only model updates, future systems can comply with data protection regulations while enabling collaborative learning across institutions. This trend aligns with the growing demand for privacy-preserving healthcare solutions.

Table 6.1: Emerging Trends in LLM-Based Healthcare Applications

Emerging Trend	Description
Multimodal AI	Combines language, speech, behavior
Personalized Models	Patient-specific cognitive baselines
Edge AI	Local, low-latency processing
Federated Learning	Privacy-preserving training
Conversational AI	Continuous cognitive monitoring

Overall, emerging trends indicate a shift toward intelligent, personalized, and preventive healthcare systems. The future applications of LLM-assisted Alzheimer's detection extend beyond diagnosis, offering continuous monitoring, risk prediction, and decision support that can significantly transform neurological healthcare.

6.2 Potential for Advancements in Sustainability

Sustainability is an increasingly important consideration in the development and deployment of AI-driven healthcare solutions. The proposed LLM-assisted early detection framework using LoRA offers significant potential for advancing sustainability across economic, environmental, and social dimensions. As healthcare systems worldwide face rising costs and resource constraints, sustainable technological solutions are essential for long-term viability.

One of the primary contributions to sustainability lies in computational efficiency. Traditional training and deployment of large language models require extensive computational resources, leading to high energy consumption and operational costs. By employing LoRA-based fine-tuning, the system minimizes the number of trainable parameters, significantly reducing energy usage and hardware requirements. This approach supports environmentally responsible AI development by lowering carbon footprints associated with large-scale model training. From an economic sustainability perspective, early detection of Alzheimer's Disease reduces long-term healthcare expenditure by enabling timely intervention and preventive care. Early diagnosis can delay disease progression, decrease hospitalization rates, and reduce dependence on intensive caregiving services. AI-assisted screening tools provide a cost-effective alternative to expensive diagnostic procedures, contributing to more efficient allocation of healthcare resources.

Social sustainability is also enhanced through equitable access to diagnostic support. Language-based AI systems can be deployed across diverse regions, including rural and underserved communities, without the need for advanced medical infrastructure. This promotes inclusive healthcare delivery and reduces disparities in access to early diagnostic services. By supporting independent living and early care planning, such systems improve patient well-being and reduce caregiver burden.

Additionally, sustainable innovation is supported through scalable and modular system design. The adaptability of LoRA-enabled models allows continuous improvement and updating without full system redevelopment. This ensures long-term usability and reduces technological obsolescence, aligning with sustainable digital transformation goals.

Overall, the integration of efficient AI techniques with healthcare applications demonstrates a pathway toward sustainable medical innovation. The proposed approach not only addresses immediate diagnostic needs but also supports long-term environmental, economic, and societal sustainability in healthcare systems.

6.3 Interdisciplinary Approaches and Innovation

The early detection of Alzheimer's Disease using LLM-assisted systems represents a highly interdisciplinary research area that integrates knowledge and methodologies from multiple domains. Effective innovation in this field requires collaboration between artificial intelligence researchers, healthcare professionals, neuroscientists, linguists, and data scientists. Such interdisciplinary approaches enable the development of solutions that are not only technically sound but also clinically relevant and socially responsible.

From a medical and neuroscience perspective, clinical expertise is essential for identifying meaningful cognitive indicators and validating AI-driven predictions. Collaboration with neurologists and psychologists ensures that language patterns and behavioural markers used by the model accurately reflect clinical symptoms of Alzheimer's Disease. This interdisciplinary input enhances the reliability and acceptance of AI-based diagnostic tools in healthcare settings.

Linguistics plays a critical role in understanding language degradation patterns associated with cognitive decline. Insights from linguists help improve feature interpretation, dataset annotation, and evaluation of semantic coherence, thereby strengthening model accuracy. Meanwhile, advances in computer science and machine learning provide the technical foundation for building efficient and scalable AI models, particularly through innovations such as LoRA and transformer-based architectures.

Innovation also emerges through the integration of human-centered design and ethical AI principles. Interdisciplinary collaboration with social scientists and ethicists helps address concerns related to data privacy, bias, transparency, and patient trust. These considerations are crucial for responsible AI deployment in sensitive medical domains.

Furthermore, interdisciplinary research fosters cross-domain innovation, enabling the extension of Alzheimer's detection methodologies to other neurodegenerative and mental health disorders. By combining expertise across disciplines, the proposed framework encourages continuous innovation and the development of holistic healthcare solutions.

In summary, interdisciplinary collaboration serves as a driving force for innovation in AI-assisted healthcare. By bridging technical advancement with medical, linguistic, and ethical insights, the proposed approach demonstrates a comprehensive and forward-looking pathway toward impactful and sustainable healthcare innovation.

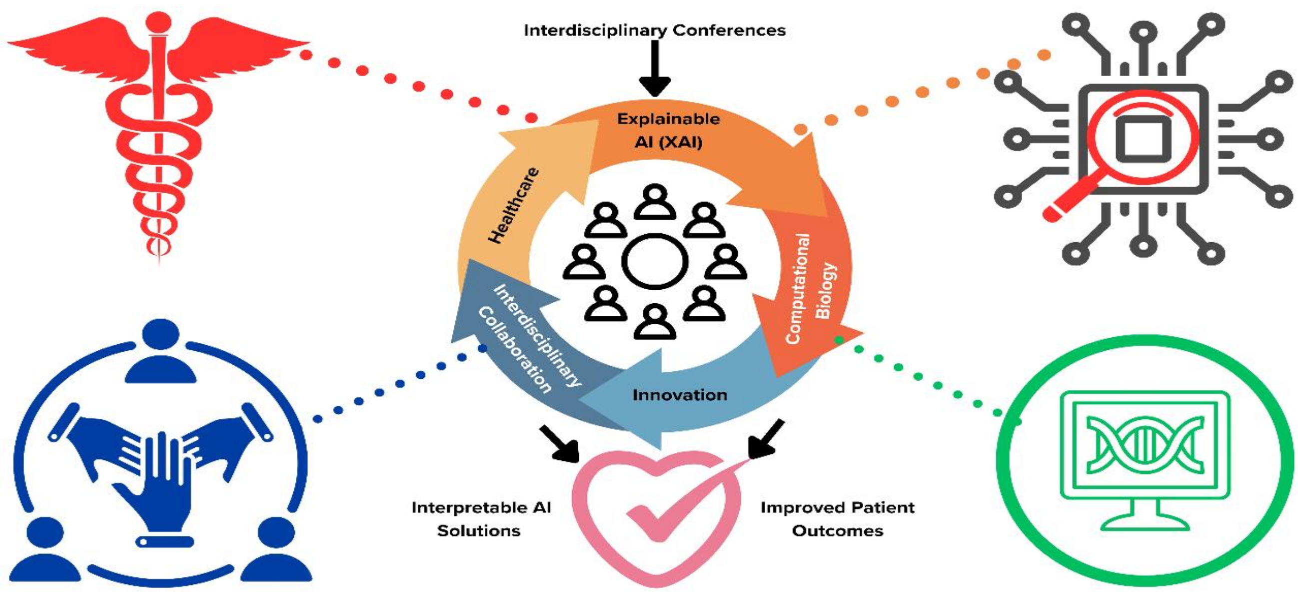

Figure 6.1: Interdisciplinary collaboration for AI-driven Alzheimer's detection

Chapter 7

CONCLUSION AND REFLECTION

This chapter presents the overall conclusion of the seminar report by summarizing the key findings, reflecting on the alignment of the proposed work with the United Nations Sustainable Development Goals (SDGs), and discussing its potential contribution to addressing global healthcare challenges. The chapter consolidates the insights gained throughout the study and highlights the broader impact and relevance of LLM-assisted approaches in sustainable and innovative healthcare solutions.

7.1 Summary of Findings

This seminar report examined the role of Large Language Models (LLMs) combined with Low-Rank Adaptation (LoRA) in enabling the early detection of Alzheimer's Disease. The study highlighted the growing global burden of Alzheimer's and emphasized the importance of early diagnosis in improving patient outcomes and reducing healthcare costs. Through an extensive review of existing literature, the report identified language impairment as a critical early indicator of cognitive decline and established the effectiveness of AI-driven language analysis in detecting such patterns.

The report explored various technical approaches, including natural language processing techniques, transformer-based architectures, and parameter-efficient fine-tuning methods. The analysis demonstrated that LoRA significantly enhances the practicality of deploying large language models by reducing computational complexity while maintaining high diagnostic performance. Existing prototypes and solutions were evaluated, revealing both their strengths and limitations in terms of effectiveness, scalability, and real-world applicability.

Furthermore, the study discussed real-world applications, societal impact, and future innovation potential, emphasizing sustainability, accessibility, and interdisciplinary collaboration. Overall, the findings confirm that LLM-assisted systems, when optimized using LoRA, offer a promising, scalable, and sustainable approach for early Alzheimer's Disease detection and decision support in modern healthcare systems.

Table 7.1: Summary of Key Findings

Aspect	**Key Insight**
Disease Detection	Language is an early indicator

Technology	LLMs improve accuracy
Efficiency	LoRA reduces computation
Scalability	Suitable for real-world use
Sustainability	Cost-effective & inclusive

7.2 Reflection on SDG Alignment

The proposed LLM-assisted early detection framework for Alzheimer's Disease demonstrates strong alignment with the United Nations Sustainable Development Goals (SDGs), particularly those related to healthcare, innovation, and social equity. Throughout this seminar report, the focus has been on developing a solution that not only addresses a critical medical challenge but also supports long-term sustainable development.

The most direct alignment is with SDG 3: Good Health and Well-Being, which emphasizes ensuring healthy lives and promoting well-being for all at all ages. Early detection of Alzheimer's Disease enables preventive care, timely intervention, and improved quality of life for patients and caregivers. By facilitating early diagnosis through non-invasive and accessible AI-based methods, the proposed approach contributes to reducing disease burden and improving healthcare outcomes.

The research also aligns with SDG 9: Industry, Innovation, and Infrastructure by promoting the use of advanced artificial intelligence technologies in healthcare. The adoption of Large Language Models and LoRA-based fine-tuning represents innovation in medical diagnostics, supporting the development of resilient and efficient healthcare infrastructure. Parameter-efficient AI solutions enable sustainable technological growth without excessive resource consumption.

Additionally, the framework supports SDG 10: Reduced Inequalities by improving access to diagnostic support in underserved and resource-limited regions. Language-based AI systems can be deployed remotely, helping bridge gaps in healthcare availability and ensuring that advanced diagnostic tools reach diverse populations.

Overall, this work reflects a strong commitment to aligning technological advancement with global sustainability goals. By integrating healthcare innovation with accessibility, efficiency, and equity, the proposed approach contributes meaningfully to the achievement of the SDGs and underscores the role of AI in sustainable global development.

7.3 Future Contribution to Global Challenges

The proposed LLM-assisted early detection framework for Alzheimer's Disease has the potential to make a meaningful contribution to addressing several global healthcare challenges. As populations age worldwide, the prevalence of neurodegenerative disorders is expected to rise significantly, placing increased pressure on healthcare systems and social support structures. By enabling early, accurate, and accessible detection, the proposed approach can help mitigate the long-term impact of Alzheimer's Disease on individuals, families, and societies.

One of the key global contributions of this work lies in its support for preventive and proactive healthcare. Early identification of cognitive decline allows for timely medical intervention, lifestyle adjustments, and long-term care planning. This shift from reactive treatment to preventive care can significantly reduce healthcare costs and improve patient outcomes on a global scale.

The framework also contributes to addressing the challenge of healthcare workforce shortages, particularly in low- and middle-income countries. AI-assisted diagnostic tools can support non-specialist healthcare providers by offering reliable screening and decision support, thereby improving diagnostic reach and efficiency. This enables better utilization of limited medical expertise and resources.

Furthermore, the emphasis on sustainable and efficient AI technologies, such as LoRA-based fine-tuning, aligns with global efforts to develop environmentally responsible digital solutions. Reducing computational and energy demands supports climate-conscious innovation while maintaining technological advancement.

Finally, the adaptable and interdisciplinary nature of the proposed approach enables its extension to other neurological and mental health conditions, contributing to broader global health resilience. By combining innovation, sustainability, and accessibility, this work demonstrates the potential of artificial intelligence to address complex global challenges and support the development of inclusive, future-ready healthcare systems.

REFERENCES

[1] Y. Zhang, X. Liu, J. Chen, and H. Wang, “Large language models for clinical natural language processing: A comprehensive survey,” *IEEE Journal of Biomedical and Health Informatics*, vol. 28, no. 2, pp. 612–628, Feb. 2024.

[2] R. Luo, L. Sun, Y. Xia, T. Qin, S. Zhang, H. Poon, and T. Liu, “BioGPT: Generative pre-trained transformer for biomedical text generation and mining,” *Briefings in Bioinformatics*, vol. 25, no. 1, pp. 1–13, Jan. 2024.

[3] L. Yuan, H. Jiang, H. Shen, L. Shi, and N. Cheng, “Sustainable development of information dissemination: A review of current fake news detection research and practice,” *Systems*, vol. 11, no. 9, pp. 458–472, Sept. 2023.

[4] S. Rastogi and D. Bansal, “A review on fake news detection 3T’s: Typology, time of detection, taxonomies,” *International Journal of Information Security*, vol. 22, no. 1, pp. 177–212, Jan. 2023.

[5] E. J. Hu, Y. Shen, P. Wallis, Z. Allen-Zhu, Y. Li, S. Wang, L. Wang, and W. Chen, “LoRA: Low-rank adaptation of large language models,” in *Proc. Int. Conf. on Learning Representations (ICLR)*, Virtual Conference, Apr. 2022.

[6] I. Ali, M. N. B. Ayub, P. Shivakumara, and N. F. B. Mohd Noor, “Fake news detection techniques on social media: A survey,” *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 9876543, pp. 1–18, 2022.

[7] A. Balagopalan, B. Eyre, F. Rudzicz, and J. Novikova, “To BERT or not to BERT: Comparing speech and language-based approaches for Alzheimer’s disease detection,” in *Proc. Annual Conf. of the International Speech Communication Association (INTERSPEECH)*, Shanghai, China, pp. 2162–2166, Oct. 2020.

[8] K. C. Fraser, J. A. Meltzer, and F. Rudzicz, “Linguistic features identify Alzheimer’s disease in narrative speech,” *Journal of Alzheimer’s Disease*, vol. 49, no. 2, pp. 407–422, 2016.

[9] J. W. Pennebaker, M. R. Mehl, and K. G. Niederhoffer, “Psychological aspects of natural language use: Our words, our selves,” *Annual Review of Psychology*, vol. 54, no. 1, pp. 547–577, 2003.

[10] H. Goodglass and E. Kaplan, *The Assessment of Aphasia and Related Disorders*, 2nd ed., ch. 4, pp. 75–120, Lea & Febiger, Philadelphia, USA, 1983.