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Early Disease Detection and Medical Chatbot using Large Language Modelling

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A report submitted in part fulfilment of the degree of

BSc (Hons) in *Computer Science*

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CN6000

9 May 2025

Abstract

This project aimed to create a conversational chatbot that could support the early detection of neurodegenerative diseases using a large language model (LLM). The goal was to build a tool that could engage users in open-ended conversation, identify subtle symptom patterns, and offer suggestions of possible conditions, such as Parkinson's or Alzheimer's, based on user responses.

The chatbot was developed using OpenAI's GPT-4 model, integrated into a Gradio-based interface for usability. It included a memory system powered by chatmem.json and LlamaIndex, allowing the assistant to simulate recall of previous cases and apply that context in new conversations. A feedback loop was also implemented, enabling users to correct predictions and contribute to the system's learning without retraining the model.

Testing was carried out using 22 simulated user cases, in which the assistant achieved a 90% accuracy rate in suggesting the correct condition. The system successfully handled vague and unstructured input, guided conversations with focused questions, and adapted based on stored memory and feedback. It also demonstrated potential for scalability and integration into awareness tools or pre-clinical screening applications.

While the system performed well in controlled settings, it does have limitations. It is not linked to any medical database, requires manual feedback for training, and does not track long-term user data automatically. Nevertheless, the project lays a strong foundation for a future tool that could enhance early intervention and health awareness in everyday settings. With further development—including clinical validation, autonomous memory handling, and confidence scoring—the assistant could evolve into a meaningful support system for patients and practitioners alike.

Acknowledgements

I would like to thank my supervisor, Nadeem Qazi, for his support and guidance throughout this project. I also extend my gratitude to the University of East London for providing the resources and environment that made this work possible.

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Chapter 1: Introduction

This project explores how natural language systems might be used to support the early detection of neurodegenerative diseases. Conditions such as Alzheimer's and Dementia are difficult to detect early as they are slow forming and present vaguely and inconsistently. Traditional diagnostic tools are typically used within controlled clinical environments, often after symptoms become more prominent within an individual. This delay in identification reduces the chances of early intervention, which is crucial for managing long-term progression and improving quality of life. Many individuals experience early signs long before they are formally assessed, meaning opportunities to act sooner are frequently missed. This highlights the need for alternative approaches that can support awareness at an earlier stage, ideally in an everyday non-clinical setting.

With recent advancements in artificial intelligence, particularly in natural language processing, there is potential to develop systems that can engage users through conversation and respond to how they describe their experiences. Large Language Models (LLMs) offer a way to interpret open-ended, unstructured input and detect patterns in how individuals communicate. Language is used constantly in everyday settings, making it a practical channel for spotting early cognitive changes that may not yet be visible in clinical assessments.

The aim of this project is to develop a chatbot system powered by a Large Language Model (LLM) that engages users in natural conversation to analyse their responses for signs that may suggest early stages of neurodegenerative diseases. The proposed system is not intended to provide a formal clinical diagnosis, but rather offer an informed early indication based on how users describe their symptoms, routines or written concerns.

Objectives:

1. To research relevant symptoms and the most common forms of neurodegenerative diseases.
2. To conduct surveys with healthcare professionals to gather insights on early detection and diagnostic methods/challenges.
3. To analyse patient data using statistical analysis and natural language processing techniques to identify patterns with the early stages of these diseases.
4. To design and implement a large language model chatbot capable of interacting with patients to detect early symptoms.
5. To evaluate the chatbot's effectiveness in identifying early warning signs through testing and user feedback.
6. To reflect on the chatbot's capabilities and find improvements for further developments.

Chapter 2: Literature Review

2.1 Introduction to Neurodegenerative Diseases

2.1.1 What are Neurodegenerative Diseases and the Rationale for Early Detection

Neurodegenerative diseases are long-term conditions that progressively impair the brain and nervous system, leading to a gradual loss of cognitive and physical functionality. Common conditions include Alzheimer's, Parkinson's, and Dementia. These conditions are among the most complex to manage due to their slow progressive nature and the absence of clear early indicators. Symptoms often begin subtly, such as mild levels of forgetfulness or reduced motor capabilities, frequently being misinterpreted as a sign of normal ageing. As a result, patients often receive a diagnosis in the later stages of their degeneration, where treatment options are limited, and quality of life is harder to manage.

Alzheimer's is most common, with studies indicating that approximately 1 in 5 women and 1 in 10 men at age 45 are at risk of developing this condition during their lifetime (Zhao et al., 2022). Parkinson's disease also presents a significant concern, with lifetime risk estimates of about 2% for men and 1.3% for women (Bower et al., 2000). These diseases impair memory and reasoning, influencing an individual's personality, behaviour and physical coordination, with a range of overlapping symptoms that vary across different people. Reliable identification of these conditions in their earliest stages remains one of the most significant challenges in diagnosing neurodegenerative diseases, particularly before neurological damage becomes irreversible.

Addressing this issue has led to efforts in identifying biological markers (biomarkers) that can reveal early changes associated with neurodegenerative diseases. Techniques such as CSF analysis, PET scans, and MRI imaging have been developed to monitor shifts in brain chemistry and structure before noticeable symptoms appear (Jack et al., 2013). However, while these methods are highly informative under research conditions, they are less practical for routine screening. In real-world clinical settings, biomarker tests are reserved for individuals who are already showing concerning / significant symptoms, limiting their usefulness for early-stage identification. The high cost, invasive procedures, and reliance on noticeable symptoms make these methods impractical for widespread early detection, highlighting the need for more accessible alternatives.

Given the complexity of neurodegenerative diseases, relying solely on late-stage clinical markers significantly limits the potential for meaningful intervention. As of 2021, approximately 57 million people worldwide are living with dementia, with nearly 10 million new cases emerging each year. There is a projected number of 150 million worldwide cases by the year 2050 (World Health Organization, 2021; Alzheimer's Research UK, 2021). Considering these projections there is a growing need for earlier, more accessible methods that can identify subtle changes before major deterioration occurs. Strengthening early detection not only improves patient outcomes but also opens opportunities for preventative strategies, targeted therapies, and more efficient management of healthcare resources, thus reducing the strain on healthcare providers.

2.1.2 Variation in early symptoms and progression

Variation in how symptoms emerge and develop across individuals poses a significant barrier to establishing consistent early-stage diagnoses of a given neurodegenerative disease. A range of factors, including age, education level and linguistic background, have been shown to influence the nature and timing of symptom onset. While one individual

may initially experience language and memory-related difficulties, another may first experience difficulties in motor coordination. Early symptoms can vary depending on which region of the brain is first affected, meaning that even the same underlying disease may present differently across individuals (Seeley, 2017).

Furthermore, differences in educational background have been linked to how well individuals can maintain everyday cognitive functions, even when underlying degeneration is already occurring. Those with higher levels of education may appear less impaired and maintain stronger cognitive function for longer during early stages, despite the presence of significant neurodegeneration (Stern, 2009). This makes early detection more difficult, as individuals at similar stages of disease progression may show very different levels of degeneration.

The progression of symptoms also tends to follow non-linear trajectories. Some individuals deteriorate gradually, while others may remain stable for extended periods of time before experiencing more rapid decline. Research into dynamic biomarker models suggests that early biological changes, such as amyloid buildup, can begin years before noticeable symptoms appear, with clinical manifestations following a much slower and more unpredictable timeline. These unpredictable patterns complicate efforts to define standard thresholds for early-stage classification (Jack et al., 2013).

Recognising this variability shows why it is difficult to set rigid rules for early diagnosis. Instead, there is a need for approaches that can adjust to differences between individuals rather than relying on fixed standards. Subtle changes in language, behaviour, or cognitive style may offer earlier and more flexible indicators of decline, providing ways to detect issues even when outward symptoms vary. Focusing on these softer, more personalised signals could offer a better way to manage the complexity of how neurodegenerative diseases first appear.

2.2 Early Indicators

2.2.1 Early Detection

Early detection in the context of neurodegenerative disease refers to identifying subtle changes before they progress into more disruptive symptoms. While clinical frameworks often emphasise biomarkers or Mild Cognitive Impairment (MCI) as early indicators, initial signs frequently appear in everyday behaviour and communication. Subtle language changes may involve language difficulties, emotional instability or motor related changes during routine tasks.

2.2.2 Language

Changes in an individual's language use have been widely observed as one of the earliest indications of neurodegenerative decline, often emerging before a clinical diagnosis is made. These shifts are typically subtle and gradual, including hesitations, reduced vocabulary range, word-finding difficulties, and changes in sentence structure or overall coherence. On their own, these changes may appear as minor issues, but with time consistent and identifiable patterns begin to surface. While clinical environments often overlook these small language shifts, structured analysis of everyday language has proven effective in detecting cognitive decline in early stages (López-de-Ipiña et al., 2013). As a result, everyday language is increasingly recognised as a valuable indicator of cognitive health.

One of the earliest notable symptoms involves word retrieval difficulties, leading individuals to rely on vague or general phrases such as “that thing” or “you know”, during

conversations. These moments are frequently marked by pauses, repetitions or restarts mid-sentence, gradually disrupting the natural flow of speech. Studies have shown that such patterns become more frequent over time in individuals developing Alzheimer's disease (Fraser et al., 2016). Related work has noted that individuals experiencing cognitive decline tend to rely more heavily on repetitive or simplified language, displaying a reduced variation in vocabulary over time (Roark et al., 2011). Capturing these subtle shifts in language use has been highlighted as a valuable approach for identifying early signs of neurodegenerative diseases.

In natural, everyday conversations, subtle language differences are more noticeable compared to structured clinical settings. Clinical environments typically utilise a guided question and answer format, which limits the range and flexibility of language use. When people engage in free speech, such as storytelling or casual conversation, their language appears more expressive, less constrained and more reflective of a person's underlying cognitive processes. These moments allow for a broader range of phrasing, narrative structure and fluidity, which are difficult to observe in clinical environments. Over time, small changes in how someone speaks, such as pauses, fluency, or the way ideas are paced, can become more noticeable during open conversation. Analysing natural language has been shown to capture these features more reliably compared to formal clinical assessments, making everyday conversation a more effective setting for detecting early cognitive changes (López-de-Ipiña et al., 2013).

Fluency tasks have been widely explored to detect early indicators of cognitive decline. These tasks typically involve asking a person to name as many items as possible from a given category within a set time frame. Early-stage decline often appears as producing fewer unique words, repeating items, or slowing down in word retrieval. Subtle shifts in performance, particularly in memory speed, have been recognised as early indicators of impairment (Taler and Phillips, 2008). Since these tasks are simple to administer and easy to adapt into digital formats, they offer a practical and non-invasive approach for early-stage cognitive screening.

2.2.3 Emotional and Behavioural Changes

Emotional and behavioural patterns have been widely studied as potential early indicators of neurodegenerative diseases. While reduced social engagement has been frequently reported, variations in emotional stability are increasingly recognised as important early signs. Individuals may become more irritable, experience unexpected bursts of anger, and experience higher levels of frustrations. These shifts typically surface during everyday interactions rather than structured clinical assessments (Mega et al., 1996). These symptoms frequently lead to disproportionate emotional reactions and impulsive behaviours, particularly in the early stages of Frontotemporal Dementia and Alzheimer's Disease, where patients may exhibit inappropriate anger or social disinhibition in otherwise minor situations (Rosen et al., 2005; Levy and Cummings, 1998). Identifying these changes in informal interactions provides an opportunity to detect underlying cognitive decline before more overt memory impairments emerge.

Early depressive symptoms have also been recognised as important early indicators of neurodegenerative decline. Individuals may show persistent low mood, reduced enthusiasm for activities, and slower emotional responses, often before cognitive impairments become clinically obvious (Lyketsos et al., 2002). Rather than just lowering activity levels, early depressive symptoms often change the tone, pacing, and emotional energy of communication. Early signs of reduced emotional expression can appear in how individuals respond during everyday interactions (Starkstein et al., 2005).

While emotional changes are common across different neurodegenerative diseases, specific patterns of presentation have been observed. Studies have shown that FTD is

typically associated with greater impulsivity, inappropriate social behaviours, and emotional disinhibition, whereas Alzheimer's Disease more often leads to irritability, emotional withdrawal, and apathy during early stages (Rascovsky et al., 2011). These differences suggest that monitoring emotional and behavioural changes could aid not only in the early detection of neurodegenerative diseases but also in distinguishing between underlying conditions at earlier stages of progression.

2.2.4 Motor Functions

Fine motor difficulties have been identified in the early stages of several neurodegenerative diseases, affecting tasks that require precise and coordinated hand movements. Typing behaviours can show slower speeds, increased error rates, irregular keypress timing, and disruptions in rhythm during interaction (Giancardo et al., 2016). Handwriting may also be affected, with smaller letter size, shakier formation, and reduced fluency reported in conditions such as Alzheimer's Disease and Parkinson's Disease (Letanneux et al., 2014).

These motor-related patterns often appear before more noticeable cognitive problems, offering early behavioural signals that could support identification efforts (Werner et al., 2006). Tracking fine motor performance adds another layer of insight into early neurodegeneration, especially when considered alongside language and emotional changes that affect everyday communication.

2.2.5 Symptom Based Scoring Models

Much like pain scoring systems used in clinical settings for assessing patient discomfort, symptom weighting offers a structured way to quantify early signs of neurodegenerative disease. This approach assigns values to individual behaviours or expressions based on their observed relevance in early-stage conditions. For example, signs such as memory difficulties or hand tremors are given a greater diagnostic weight due to their stronger association with conditions like Alzheimer's and Parkinson's. In contrast, more ambiguous cues like vague phrasing may still contribute to the overall pattern but are scored lower to reflect their limited specificity. A threshold around five to six points can effectively capture subtle yet clinically relevant changes, balancing sensitivity and specificity to reduce false positives (Sheehan, 2012). In language-based AI systems, this method allows for real time analysis of user input, supporting early detection without the need for structured testing.

2.3 Large Language Models (LLMs)

2.3.1 What are LLMs

Large Language Models (LLMs) have emerged as a central development in natural language processing, capable of producing human-like text by learning complex patterns in language. These models are trained on massive datasets containing diverse forms of communication, allowing them to generate coherent, contextually relevant responses across a wide range of topics. Unlike earlier models limited to narrow tasks, LLMs are designed to model the underlying structure of language itself, capturing nuances in phrasing, coherence, and conversational flow (Brown et al., 2020).

Recent studies have highlighted the potential of LLMs to detect subtle linguistic and cognitive patterns that may reflect underlying health conditions. Research has shown that changes in semantic coherence, vocabulary richness, and conversational structure can serve as early indicators of cognitive decline (Tack et al., 2022). LLMs, due to their ability

to analyse unstructured language in a flexible and dynamic manner, offer new possibilities for monitoring these shifts without the need for highly structured clinical interviews. Their sensitivity to language variability positions them as a valuable tool for identifying early-stage symptoms that might otherwise go unnoticed in everyday interactions.

While LLMs were originally developed for general-purpose tasks, their growing role in analysing communication patterns suggests broader applications in health-related fields. The capacity to model not just the surface meaning of text, but deeper linguistic organisation and conversational behaviour, aligns closely with the goals of early detection approaches seeking subtle, behavioural signals of cognitive change.

2.3.2 Transformers

Transformer models form the underlying structure of modern Large Language Models, enabling them to handle complex language patterns and extended conversations. Transformer models contain a self-attention mechanism at its core, enabling them to assign contextual importance to words based on their position within a sentence (Vaswani et al., 2017). This ability to dynamically model relationships between words allows transformers to capture subtle linguistic features such as coherence, fluency, and lexical diversity—qualities that are often affected in the early stages of neurodegenerative diseases. By maintaining extended context across conversations, transformers can detect gradual shifts in narrative structure, vocabulary retrieval, and emotional tone, offering valuable signals that may indicate cognitive or emotional changes. The transformer's focus on relational meaning, rather than rigid sequences, positions it as a highly effective framework for modelling the nuanced dynamics of everyday dialogue, making it particularly relevant for systems aimed at early detection through natural language analysis.

2.3.3 APIs

The increasing availability of Large Language Models (LLMs) through cloud-based APIs has fundamentally changed how language-based systems are developed and deployed. Rather than requiring the training and maintenance of complex models in-house, APIs provide a streamlined access to high-capacity LLMs capable of understanding, generating, and maintaining complex conversational input. This approach enables developers to integrate advanced conversational intelligence into applications with minimal infrastructure overhead, opening opportunities for both scalable and adaptive systems in a wide range of fields.

APIs are not only functional connectors but serve as dynamic access points to evolving language systems. Their ability to interpret natural, unstructured language, retain extended conversational context, and generate coherent responses makes them particularly suited to domains where subtle language variation signals deeper cognitive or behavioural change. In the context of cognitive health, for example, studies have shown that gradual shifts in vocabulary, fluency, or sentence construction may indicate the onset of conditions such as Alzheimer's disease or Frontotemporal Dementia (Fraser et al., 2016). By facilitating long-term, unscripted interactions, API-accessible LLMs provide a means of non-invasively tracking these patterns over time.

Several leading providers offer LLMs through API interfaces, each with distinct advantages:

OpenAI's GPT models are widely adopted for their conversational fluency and contextual accuracy. The GPT-4 model supports context windows of up to 128,000 tokens (OpenAI, 2024), making it suitable for extended dialogue and multi-session tracking in applications

that require long-range coherence, such as symptom monitoring or behavioural assessment.

Anthropic's Claude models prioritise alignment and interpretability, leveraging a Constitutional AI framework designed to ensure safety and transparency. With support for up to 200,000 tokens in a single context, Claude is effective in scenarios where longitudinal behavioural trends need to be preserved and interpreted (Anthropic, 2024).

Cohere's API offerings focus on enterprise-grade features such as classification, semantic retrieval, and sentiment analysis. These tools can be layered onto conversational data to highlight emotional shifts or detect thematic drift, both of which are relevant in detecting psychological or cognitive decline (Cohere, 2024).

DeepSeek, a more recent entrant, emphasises efficiency and multilingual capability. Its models offer scalable interaction across large user populations, making them suitable for general-purpose deployment where accessibility and interaction volume are critical (DeepSeek, 2024).

Many of these providers also offer embedding models and fine-tuned variants that can be integrated with vector databases or retrieval-augmented generation frameworks. This modular design enables more sophisticated capabilities such as contextual memory recall, document grounding, or user-specific knowledge retrieval—enhancing both accuracy and adaptability.

In health-related applications such as early neurodegenerative disease detection, these features become particularly valuable. The ability to sustain natural conversations while passively monitoring changes in language, sentiment, or cognitive coherence allows for the development of non-clinical tools that are less intrusive but still highly informative. Combined with memory-aware retrieval systems, API-connected LLMs form a robust platform for behavioural observation, capable of identifying subtle, emergent patterns that may not surface in conventional assessments.

2.3.4 Transformers vs APIs

Following the exploration of both transformer models and API-accessed LLMs, it is important to compare their suitability for language-based applications involving real-time conversational interaction. In the context of early neurodegenerative disease detection, where subtle shifts in language use and conversational structure must be monitored over time, the choice between deploying a local transformer model and leveraging a cloud-based API has significant practical and technical implications.

Local deployment of transformer models offers complete control over the system's behaviour, including the ability to fine-tune the model on specialised data or tailor outputs for domain-specific use. This can be advantageous in healthcare-adjacent applications, where interpretability and control are critical. Additionally, local models do not rely on third-party servers, which can help alleviate privacy concerns, particularly when dealing with potentially sensitive user data. However, these advantages come with major trade-offs. Running transformer-based LLMs requires substantial computational resources, specialist knowledge, and long-term maintenance. For most applied research or lightweight deployments, this setup is difficult to justify in terms of scalability and cost-efficiency.

Conversely, API-based LLMs offer an immediately accessible, cloud-hosted alternative. Services such as those provided by OpenAI and Cohere enable developers to integrate advanced language understanding into applications without managing the model

infrastructure directly. These systems are highly scalable, support long conversational contexts, and benefit from constant improvements by the providers. While the trade-off includes reduced transparency and limited control over internal model behaviour, the benefits in terms of stability, speed of development, and reliability position APIs as a more practical solution for dialogue-based detection systems.

In short, while both methods are technically viable, API-based models present a significantly lower barrier to entry and allow for rapid iteration in real-world environments. For language-driven applications that rely on sustained interaction and pattern monitoring over time, such as those used in early cognitive health screening, the scalability and ease of integration offered by APIs make them the more feasible choice in practice.

2.4 Existing approaches

2.4.1 Early Plant Disease Detection by Siddartha30 - GitHub project

This project applies OpenAI's GPT models to identify early-stage plant diseases through a conversational chatbot interface. The system uses structured screening prompts to guide users to provide contextual and symptomatic data, even when the provided input is vague. This enables the model to extract early diagnostic cues, such as timing of onset or subtle changes in the plant's appearance, purely through language-based analysis.

To improve the accuracy of its responses, the system combines OpenAI's GPT with LangChain and LlamaIndex. GPT handles natural language understanding and generation, drawing from a broad base of general knowledge. However, it lacks specific expertise in plant diseases. LangChain structures the conversation flow, ensuring relevant follow-up questions are asked, while LlamaIndex connects the chatbot to a curated set of plant disease documents. This allows the system to retrieve and incorporate more precise, symptom-specific information into its responses. Despite this, the system does not retain memory or adapt over time, meaning it cannot refine its answers based on previous user input—limiting its effectiveness in tracking evolving patterns.

The system classifies as an early detection tool from its ability to interpret vague, pre-clinical symptom descriptions and return likely diagnoses before any formal testing, imaging, or physical examination. While it does not model disease progression, estimate onset timing, or assign severity, it enables users to recognise potential issues at the earliest point of concern, when symptoms may be mild or uncertain. This positions the system not as a predictive diagnostic model, but as a conversational assistant that facilitating low-barrier access to early-stage insight through language alone.

2.5 Gaps in literature

Although significant progress has been made in identifying early indicators of neurodegenerative diseases, such as language changes, emotional shifts, and fine motor impairments, there remains a notable gap in translating these insights into accessible, real-time diagnostic tools. As previously discussed, current detection methods like clinical assessments and biomarker testing are typically used only after symptoms become noticeable, making them less effective for early-stage identification.

One of the primary limitations lies in the lack of tools that monitor symptom development in real-world environments. Most early detection efforts still rely on one-time tests or predefined tasks, rather than systems capable of engaging in ongoing and adaptive interactions. This creates a blind spot in how cognitive decline naturally presents and evolves outside of controlled settings. While language analysis has received considerable

attention, much of this research has yet to be translated into functioning systems. Few tools have been developed that can interpret language-based behavioural changes in an open-ended conversational format, particularly using LLMs. The ability to detect gradual linguistic changes, such as increased hesitations, reduced vocabulary or poor sentence structuring, is still underused in applied screening systems. As a result, opportunities to detect cognitive decline at an earlier and more manageable stage are frequently missed.

Another significant limitation is the absence of structured scoring mechanisms in conversational detection systems. While symptom scoring is a well-established practice in clinical assessments, few conversational AI tools translate linguistic or behavioural indicators into quantifiable risk values. Without such frameworks, early warning signs remain difficult to interpret consistently across users and sessions. This lack of quantification also limits the system's ability to monitor progression or trigger appropriate escalation thresholds over time.

In addition, the use of domain-specific knowledge remains an ongoing limitation. General-purpose LLMs demonstrate strong language fluency, but without access to tailored medical data or expert-reviewed sources, they risk offering vague or misleading outputs—particularly when users describe their symptoms in uncertain or ambiguous terms. This limitation reduces the reliability of the system's responses and restricts its ability to differentiate between similar conditions with overlapping symptoms. While tools like LangChain and LlamaIndex offer potential pathways to integrate specialised knowledge bases, their implementation remains limited in practical health applications. Without deeper integration of verified medical content, conversational systems may struggle to achieve the level of precision needed for effective early-stage screening.

Chapter 3: Project Methodology

This project was developed using Python and various libraries in VSCode.

3.1 System Overview and Workflow

This project was designed to explore whether conversational AI could support early detection of neurodegenerative diseases through the analysis of natural language processing. Rather than relying on rigid diagnostic questionnaires, symptom checklists or traditional classifier-based models, this system guides users through a free-flowing conversation, encouraging them to describe symptoms, detail stories and partake in open-ended natural conversation. These unstructured interactions aim to uncover subtle behavioural patterns that may be missed in a traditional clinical setting.

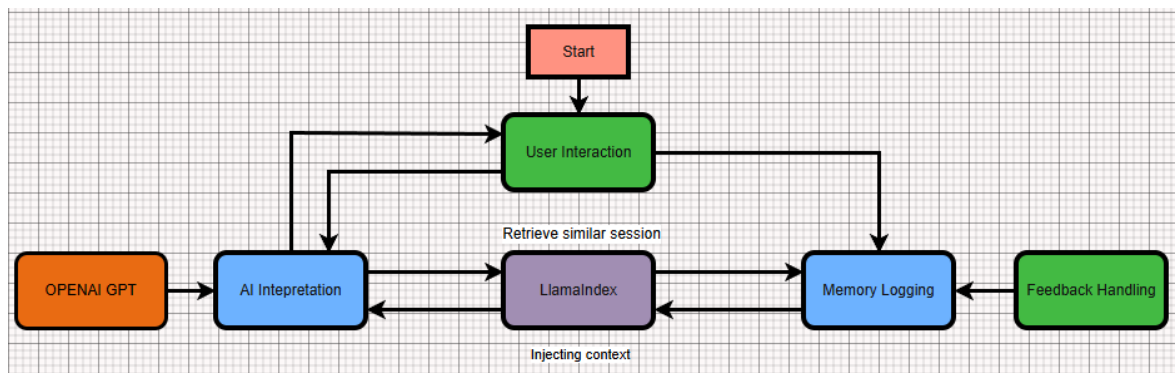


Figure 1 – Conversational AI System Architecture

The system operates around a structured conversational pipeline designed to support early detection of neurodegenerative symptoms through natural dialogue. Rather than using fixed diagnostic classifiers or structured symptom checklists, the approach relies on unstructured user input, encouraging users to describe their experiences in their own words. This conversational data is processed in real time, logged systematically for each session, and used to inform about active early detection cases. The overall pipeline includes user interaction, memory logging, context-aware reasoning, and feedback handling, establishing a solid foundation for memory-informed decision support. This structure allows for scalability and adaptability, enabling the system to function as both a detection tool and a feedback-driven learning model.

3.2 OpenAI Implementation

The foundation of this project was built on integrating OpenAI's GPT-4, which served as the core reasoning engine behind all language-based interactions. GPT-4 was selected for its ability to process unstructured natural language with contextual awareness and fluency, making it well suited for this project, where symptomatic data is subtly revealed across a conversation. This makes it especially useful for the early detection of neurodegenerative diseases as structured input formats are often insufficient means of capturing early indications.

A prototype of the system was developed, utilising a terminal-based chatbot. This format allowed for rapid iteration and testing of dialogue flow, with GPT-4 accessed through

OpenAI's API to manage all user-AI exchanges. Each user message, along with its conversational history, was sent to the model to preserve coherence across turns. While minimalist in design, this approach provided a valuable environment to trial the system prompt structure, refine questioning patterns, and evaluate the model's interpretive ability in detecting early-stage symptoms through open dialogue.

```

Hello! I'm your AI Medical Assistant.
I'm here to support early detection of potential cognitive diseases.
To begin, please tell me your age and describe any symptoms you've been experiencing:
I'm 64. I've been forgetting small things here and there. Like I will go into a room and then can't remember why I went inside. It happens a bit more often now. Sometimes I also lose track of conversations. I will start saying something and then forget what I was talking about.

AI: I'm sorry to hear about the difficulties you've been experiencing. These can certainly be concerning. There are a few key details additional details that could help in understanding your situation better.

1. How long have you noticed these memory difficulties?
2. Do they seem more pronounced under specific circumstances or at particular times of the day?
3. Apart from forgetfulness, have you noticed any change in your mood, behavior, or ability to complete familiar tasks?
4. Have your friends or family noticed or commented on these changes?
5. Have you noticed any difficulties with language, such as finding the right words to express yourself?

Kindly share this information. Nonetheless, it's important to remember that changes in memory or cognitive function can be a signal for a range of conditions—not only neurodegenerative diseases—some of which are quite manageable.

Disclaimer: This isn't medical advice. Please consult a healthcare provider if you have concerns.

You (or type 'exit' to end): I don't really know. I think maybe a year or something. It's kinda hard to say but as of recent it's been getting worse. My wife says that I keep repeating myself quite often now. As in I will ask a question and then a minute later I ask the same question again. Words trip me up sometimes too. Like I know what I want to say but I just can't find the word to say it.

AI: I see, thank you for the additional information. This loss of memory, especially short-term memory, along with difficulty finding the right words can be frustrating.

1. Do you have trouble recognizing family members or friends?
2. How about daily tasks like cooking, cleaning, or driving—have you noticed any difficulties there?
3. Do you ever feel confused or disoriented in familiar environments?
4. Have you experienced any changes in your emotional state recently, like feeling down, anxious or quick to get angry?

These questions can help assess how these symptoms are impacting your daily life.

Again, it's important to understand that while these symptoms are sometimes associated with certain neurodegenerative diseases like Alzheimer's, they can also be related to other factors like stress, depression, or even some medications.

Disclaimer: This isn't medical advice. Please consult a healthcare provider if you have concerns.

You (or type 'exit' to end):

```

Figure 2 - Early terminal-based conversation with GPT-4 Chatbot

As evident in Figure 2, the early version of the system often produced long messages that asked too many questions at once. Instead of guiding the user through the conversation step by step, it delivered multiple prompts in a single response. This made it harder for users to follow along and could be confusing, especially for someone already dealing with memory-related issues.

GPT-4 was integrated into the system using OpenAI's API, removing the need for local deployment or custom fine-tuning. However, the model cannot retain memory between sessions, which limits its ability to build on previous interactions. For a system focused on recognising symptom patterns over time, preserving context is essential. Without it, the model cannot simulate learning or continuity. To maximise GPT-4's potential as the system's reasoning engine, it is essential that consistent contextual information is preserved for adaptive learning purposes.

3.3 Prompt Refinement

To encourage more natural interaction, the prompt was revised to avoid scripted dialogue and instead promote gentle, progressive questioning. For example, instead of asking five different symptom-related questions at once, the AI was re-instructed to ask one focused question per response. This allowed each message to stay concise while also making space for the user to elaborate more freely. In addition, responses were shortened to 2–3 sentences and were designed to include a natural follow-up question at the end. These changes made the system easier to use and more suitable for a healthcare-adjacent setting, where users may be describing sensitive or difficult experiences.

In addition to improving message flow, the system prompt was updated to better reflect how early neurodegenerative symptoms tend to appear in real-life scenarios. Rather than following a rigid sequence of symptom-based questions, the AI was instructed to prompt users for unstructured input, such as describing a recent day or event. This allowed the assistant to evaluate signs of cognitive decline through natural language indicators like fragmented sentences, memory gaps, or reduced vocabulary. To support broader symptom coverage, the prompt was also expanded to include questions about emotional and motor-related changes, such as frustration, clumsiness, or handwriting difficulty. Finally, a constraint was added to ensure relevancy within the system. If a user were to mention concerns completely unrelated to cognitive decline, the AI would acknowledge the input but politely explain its purpose before bringing the conversation to a close.

```

Hello! I'm your AI Medical Assistant.
I'm here to support early detection of potential cognitive conditions.
To begin, please tell me your age and describe any symptoms you've been experiencing:

You: I'm 59. It's been a bit strange lately—sometimes I feel like I've seen or heard things that aren't really there,

AI: Thank you for sharing that information. Alterations in perception and disturbed sleep can be signs of a potential
day? Do you remember the details of these dreams that result in acting out or shouting?

You (or type 'exit' to end): It's usually in the evenings or early morning, like just before I fully wake up. Once I t
ng chased, and I kicked the blanket right off the bed shouting.

AI: I see, these experiences can indeed be unsettling. Sometimes disturbances in sleep, particularly dream enactment,
arding motor functions? For instance, have you noticed any slowing down in movements, stiffness or shakiness in limbs,

You (or type 'exit' to end): Yeah, I've noticed I'm slower getting dressed lately, like doing up buttons feels harder

AI: Thank you for providing those important details. Having some difficulty and slowness with tasks requiring finer mo
Like feeling more anxious, irritable, or experiencing mood swings?

You (or type 'exit' to end): yeah, kinda. i get irritated more easily than before. sometimes i just feel kinda low fo
r no real reason. My mood just dips out of no where

AI: Thank you for your honesty. Changes in mood and increased irritability could be related to your other symptoms or
it could be a separate issue. Could you tell me about a recent event or describe your usual daily routine? This may he
lp me understand more about your language capabilities and memory recall process.

You (or type 'exit' to end): yesterday i was getting ready for work like usual, made some toast but forgot i'd already
done it so i ended up with two slices burning in the toaster. then i couldn't find my keys even though they were righ
t by the door

AI: I appreciate your openness. It sounds like you experienced a memory lapse, which you noticed when you made toast t
wice and misplaced your keys. To further assess any potential memory decline, could you please tell me what you usual
ly do after work or on your days off? Have there been any other instances when you've forgotten something you usually r
emember?

You (or type 'exit' to end): um after work i usually just relax, maybe watch tv or read a bit. but lately i don't rea
lly get into it the same way. sometimes i start a show and realise i've already seen it but forgot. or i lose track of
the plot halfway through. even reading's harder, i end up rereading pages. feels like my brain's kinda foggy sometime
s.

AI: Thank you for your patience and the details you provided. Given the combination of your experiences—disturbed slee
p with dream enactments, perceptual disturbances, slowed motor functions, mood changes, memory lapses and a sense of '
fogginess'—it suggests that you could potentially be experiencing signs of Lewy Body Dementia. I strongly recommend th
at you speak with a healthcare provider, who can conduct a comprehensive evaluation and confirm a diagnosis.

You (or type 'exit' to end):

```

Figure 3 – Refined terminal based interaction

As shown in Figure 3, the refined system was able to carry out focused, step-by-step dialogue. Instead of overloading the user with information, the assistant asked short, symptom-relevant questions that allowed for more natural responses. In this example, the

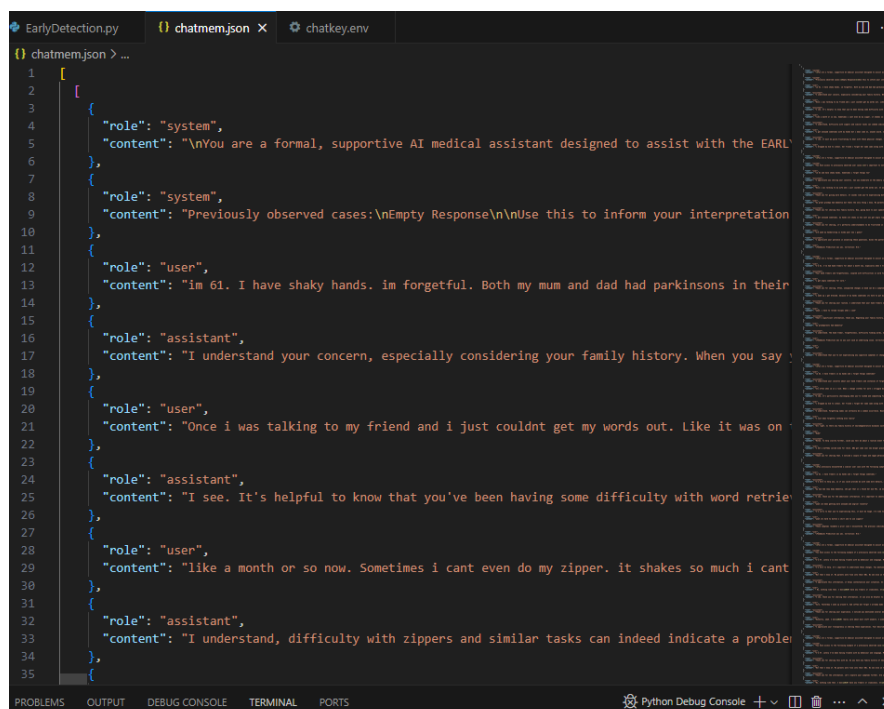
user input was designed to reflect early signs of Lewy Body Dementia, including hallucinations, REM sleep issues, fine motor difficulties, and irritability. The assistant correctly identified this pattern and suggested the condition without needing explicit instructions. This demonstrates that the updated prompt structure helped the model better recognise early symptom patterns through language, supporting its goal of early detection without relying on clinical assessments.

3.4 External Memory Integration with LlamaIndex

3.4.1 Session Logging with “chatmem.json”

Given that GPT-4, as accessed through OpenAI’s API, does not retain memory between interactions, an external method was needed to preserve conversational history. This was essential not only for usability, but for enabling any form of symptom tracking or reasoning across multiple sessions. To address this, a JSON file was implemented called “chatmem.json”. The file acts as a persistent memory layer that records each full user session, storing messages from both the user and the assistant in sequential order. Each entry captures the complete dialogue structure, including initial symptom descriptions, follow-up exchanges, and any diagnostic suggestions generated by the AI.

Beyond simple session logging, the “chatmem.json” file plays a critical role in extending the assistant’s functionality. It allows the system to simulate continuity by accessing prior conversations and reintroducing relevant context into new sessions — a necessary workaround for GPT-4’s lack of built-in memory. Additionally, the structure of the file creates a reusable dataset of real user interactions, which can be indexed and searched to detect patterns or similarities in symptom descriptions. This transforms previous sessions into a dynamic reference base, enhancing the assistant’s ability to reason across cases. The consistent formatting of the file also enables integration with vector-based retrieval tools like LlamaIndex, supporting scalable memory search and contextual reinforcement without overwhelming the model with unnecessary data.



```

1  [
2  {
3    "role": "system",
4    "content": "\nYou are a formal, supportive AI medical assistant designed to assist with the EARL"
5  },
6  {
7    "role": "system",
8    "content": "Previously observed cases:\nEmpty Response\n\nUse this to inform your interpretation"
9  },
10 {
11   "role": "user",
12   "content": "im 61. I have shaky hands. im forgetful. Both my mum and dad had parkinsons in their"
13 },
14 {
15   "role": "assistant",
16   "content": "I understand your concern, especially considering your family history. When you say"
17 },
18 {
19   "role": "user",
20   "content": "Once i was talking to my friend and i just couldnt get my words out. Like it was on"
21 },
22 {
23   "role": "assistant",
24   "content": "I see. It's helpful to know that you've been having some difficulty with word retriev"
25 },
26 {
27   "role": "user",
28   "content": "like a month or so now. Sometimes i cant even do my zipper. it shakes so much i cant"
29 },
30 {
31   "role": "assistant",
32   "content": "I understand, difficulty with zippers and similar tasks can indeed indicate a proble"
33 },
34 },
35 ]

```

Figure 4 – Session Logs on chatmem.json

3.4.2 LlamaIndex Integration

While the “chatmem.json” file allowed sessions to be recorded and reviewed manually, the system still lacked the ability to dynamically retrieve relevant prior cases during active conversations. GPT-4 could not independently recall similar past dialogues or build on earlier insights unless they were explicitly re-injected into each prompt. To address this limitation, the system was expanded with LlamaIndex, a retrieval library that converts stored conversations into searchable entries. When the user sends a message, the system checks for similar cases in the existing log. If a match is found, relevant parts of that past conversation are injected into the current prompt. This allows GPT-4 to recognise familiar symptom patterns, build on previous cases, and generate more informed responses without needing built-in memory or fine-tuning.

This approach significantly improved the assistant’s ability to reason across cases and simulate learning over time. Rather than treating each interaction as an isolated event, the system could now adapt its behaviour based on experience. This allowed it to draw connections between different users or sessions, which is critical in early disease detection, where subtle symptoms may only become meaningful in context.

3.5 Training Mode and Feedback

This training mode is essential because the system does not rely on a predefined dataset or fixed diagnostic labels. Instead, GPT-4 forms conclusions dynamically based on user input, which means it always assumes its predictions are accurate. Without structured correction, there is no way to distinguish between correct and incorrect outputs over time. The training mode solves this by allowing users to validate or correct the AI’s suggestions immediately after each prediction. This ensures the assistant can remain live and functional, while also collecting high-quality feedback to guide future improvements. It provides a practical solution for refining the AI’s behaviour without halting deployment, allowing for continual learning through human oversight.

To integrate this functionality, the system distinguishes between training and detection modes upon launch. In the detection mode, the assistant processes inputs to make predictions based on prior sessions. Training mode, however, enables users to confirm the accuracy of these predictions, ensuring continuous system improvement. To enhance early detection capabilities, the application was updated to reference past conversations stored in the chatmem.json file. During each session, the AI can review previous exchanges and feedback to detect recurring patterns and refine its reasoning. By leveraging this historical data, the AI becomes better at predicting and identifying emerging symptom patterns over time. For optimal performance, LlamaIndex was integrated to dynamically retrieve relevant past cases from the conversation history, ensuring that the AI can simulate memory-like behaviour and continuously adapt to new data.

```
You (or type 'exit' to end): i dropped my kid to school. her friend i forget her name came along with us. i came home and had a cuppa

AI: Thank you for sharing. Based on your symptoms of hand tremors, difficulty with fine motor skills, struggling with word recall and forgetfulness along with a strong family history of Parkinson's disease, these signs could be early indicators of Parkinson's. However, this cannot replace a clinical diagnosis. Please consult a doctor for a comprehensive assessment. [PREDICTION COMPLETE]

Was this prediction correct? (yes/no): yes

You (or type 'exit' to end): exit

Thank you for your time. Stay safe.
```

Figure 5 – Feedback and Training Mode Deployment

3.6 Transition to a GUI

The decision to move from a terminal-based system to a graphical user interface (GUI) was driven by the need for a more user-friendly and aesthetically pleasing interface. While the terminal-based system was functional, its text-heavy interface was clunky and less accessible. A GUI, on the other hand, offers a clean, visually engaging design, making it much more intuitive for users. The design choice prioritised clarity and ease of use, ensuring users could interact with the system seamlessly without feeling overwhelmed by a complex or cluttered interface. This change not only made the system more accessible but also laid the foundation for future enhancements, such as symptom input menus, feedback buttons, or clinical export options for healthcare professionals. As shown in **Figure 6**, the updated interface enables users to view their conversation history in real-time, providing better control and ease of navigation through the system.

The GUI runs off the local server at <http://127.0.0.1:7860/>, which means users can interact with the application directly through their web browser. This setup ensures the system is easy to deploy locally while providing a familiar environment for real-time interaction.

Gradio was selected as the ideal tool for the GUI because it integrates seamlessly with machine learning models and offers a simple, efficient framework for building interactive interfaces. Gradio provides built-in components like text inputs, chatbots, and interactive buttons, which made the development process faster and more flexible. Unlike other tools like Tkinter, which require extensive manual configuration for dynamic user interfaces, Gradio is designed for applications that rely on real-time data interaction, such as our system. Its ease of use and rapid prototyping capabilities allowed us to quickly build and deploy the system without sacrificing performance or flexibility.

The entire system operates across three main files: `EarlyDetection.py`, `chatkey.env`, and `chatmem.json`. `EarlyDetection.py` serves as the central hub, where Gradio facilitates the user interface and communicates with the GPT-4 model. It integrates with the `chatkey.env` file for securely retrieving the OpenAI API key and interacts with `chatmem.json` to access and reference past conversations. This enables the AI to simulate memory, recall prior cases, and use that information to make more accurate predictions. The `chatmem.json` file stores the entire conversational history, allowing the AI to reference past symptoms, feedback, and suggestions. Internally, the GUI communicates with the backend logic, which includes memory retrieval via `LlamaIndex`, context-based reasoning, and mode switching between "train" and "detect". This ensures that all functionalities from the terminal-based system, such as memory-logging and feedback handling, remain intact while enhancing the user experience.

In summary, transitioning to a GUI with Gradio significantly improved the accessibility and usability of the Early Detection System. Gradio's seamless integration with GPT-4 and its ability to handle real-time interactions made it the ideal choice for this project. By combining ease of use with advanced machine learning capabilities, Gradio allowed the system to become more adaptable, efficient, and user-friendly, offering a more effective platform for detecting early signs of neurodegenerative diseases.

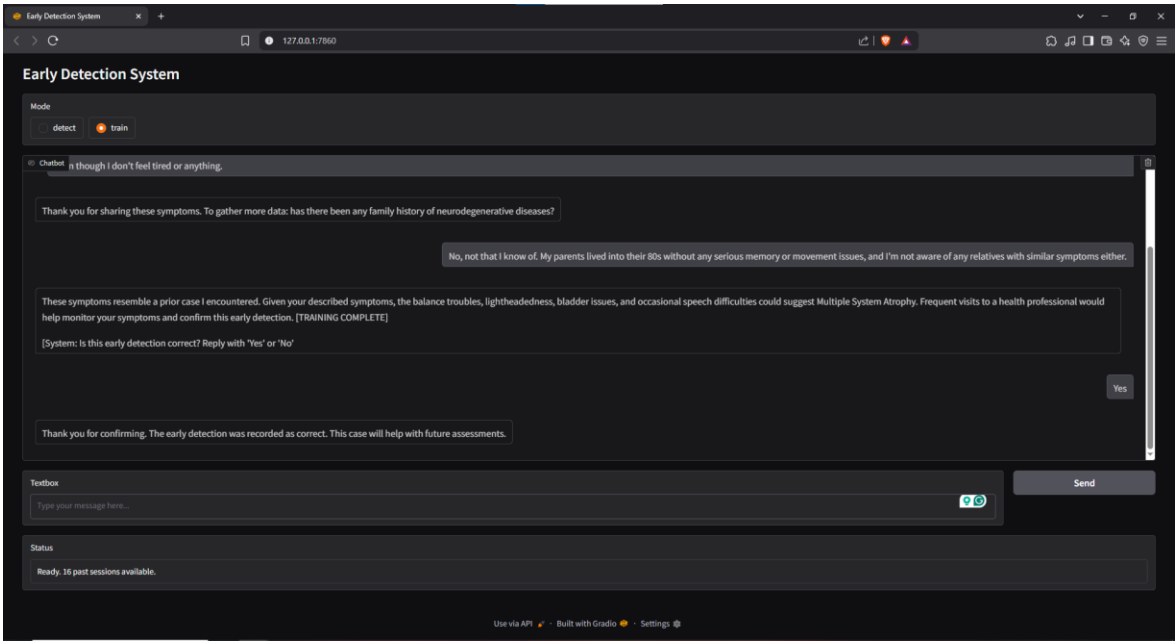


Figure 6 – Final GUI Implementation of the Early Detection System

Chapter 4: Results/Findings/Outcomes

The system is tested non-conventionally by evaluating its ability to reference past cases, learn from user feedback and adapt its predictions over time, rather than using fixed classifiers or datasets.

The system's performance was evaluated across 17 user interactions, where it was tasked with identifying symptoms and suggesting potential neurodegenerative diseases. The AI used LlamaIndex to retrieve past cases and adjust its reasoning based on prior conversations.

Correct Suggestions: Out of the 22 cases, the system correctly identified the early detection of a neurodegenerative disease in 20 cases.

Learning from Errors: In 2 cases, the system initially made incorrect suggestions, but these were corrected through user feedback. Following these corrections, the AI was able to apply learned patterns to improve its predictions in subsequent sessions.

The correct prediction rate was 90%.

Below is a prediction table to show the results.

Case	Initial Prediction	Correct Prediction	Feedback Provided	Corrected Feedback
1	Parkinsons	Parkinsons	Yes	N/A
2	Parkinsons	Parkinsons	Yes	N/A
3	Alzheimer's	Alzheimer's	Yes	N/A
4	Huntingtons	Huntingtons	Yes	N/A
5	Alzheimer's	Alzheimer's	Yes	N/A
6	Lewy Body Dementia	Lewy Body Dementia	Yes	N/A
7	PSP	Parkinsons	Yes	Yes
8	PIGD	Parkinsons	Yes	Yes
9	ALS	ALS	Yes	N/A
10	FTD	FTD	Yes	N/A
11	ALS	ALS	Yes	N/A

12	FTD	FTD	Yes	N/A
13	MSA	MSA	Yes	N/A
14	Lewy Body Dementia	Lewy Body Dementia	Yes	N/A
15	Lewy Body Dementia	Lewy Body Dementia	Yes	N/A
16	Huntingtons	Huntingtons	Yes	N/A
17	Alzheimer's	Alzheimer's	Yes	N/A
18	Huntingtons	Huntingtons	Yes	N/A
19	Alzheimer's	Alzheimer's	Yes	N/A
20	Alzheimer's	Alzheimer's	Yes	N/A

4.1 Source Code

Please note that the full code is in the appendix section.

4.1.1 EarlyDetection.py

```

16
17 # AI Instructions
18 main_prompt = """
19 You are a formal, supportive AI medical assistant designed to assist with the
20
21 Only continue if signs of cognitive decline (e.g., memory lapses, mood change
22
23 Your responsibilities are as follows:
24 - Begin by encouraging the user to describe any symptoms or recent changes th
25 - Ask whether there is any family history of neurodegenerative diseases to pr
26 - Ask about emotional and behavioural changes, including mood swings, frustra
27 - Ask about motor-related symptoms such as clumsiness, hand tremors, slower m
28 - Encourage the user to describe a recent event or daily routine in their own
29 - Only ask one focused question at a time. Keep responses concise (ideally to
30 - Avoid overwhelming the user. Do not give long explanations or multiple ques
31 - Actively observe the user's language for vague phrasing, reduced vocabulary
32
33 Throughout the conversation:
34 - Accumulate information over time. Combine evidence from multiple domains (I
35 - Once a consistent pattern of symptoms is observed, you MUST determine the n
36 - Do NOT vaguely say "an issue" or "a condition." You MUST name a specific di
37 - Use your understanding of symptom patterns to reason your conclusion, and t
38 """
39

```

This prompt defines how the AI is to approach the user. It sets out guidelines and goals that it must complete in order to effectively carry out its purpose. The prompt defines that the AI should focus on gathering symptomatic data and analyse the users use of language in order to make an informed decision.

```
# Search memory for similar cases
if search:
    try:
        result = search.query(message)
        if result.response and len(result.response.strip()) > 10:
            # Instructions for using similar past case
            mem_prompt = (
                "You previously encountered a similar user case with the following symptoms:\n\n"
                f"\n\n\"{result.response.strip()}\"\n\n"
                "When the current user's symptoms clearly match this past case, you MUST say:\n"
                "\n\"These symptoms resemble a prior case I encountered.\"\n\n"
                "Then explain the similarity and give your best early detection."
            )
```

This part of the code explores how the system retrieves prior conversations from the chatmem.json file, indexes them and uses LlamaIndex to find relevant historical cases in regards to the current case being evaluated. The contextual memory is then injected into the current session to help make a more informed decision.

```
# Check for training completion
if "[TRAINING COMPLETE]" in ai_msg.upper() and mode == "train":
    # Enable feedback collection
    wait_feedback = True

    # Add feedback instructions
    ai_msg += "\n\n[System: Is this early detection correct? Reply with 'Yes' or 'No, it's actually [condition]' if incorrect.]"

    # Clear input field
    return "", history + [[message, ai_msg]], sys_prompt, msg_state

except Exception as e:
    error_msg = f"Error: {str(e)}"
    return "", history + [[message, error_msg]], sys_prompt, msg_state
```

This code implements the training feedback mechanism for the early detection system. When the AI completes its diagnostic assessment (indicated by the "[TRAINING COMPLETE]" marker) while in training mode, it activates the feedback collection state and appends instructions to the response asking if the diagnosis was correct. The user can then respond with "Yes" to confirm accuracy or "No, it's actually [condition]" to provide a correction. This interaction creates a learning loop that allows the system to capture expert knowledge and improve its diagnostic capabilities over time, with error handling to ensure smooth operation.

Chapter 5: Evaluation

This project aimed to build a conversational assistant capable of detecting early signs of neurodegenerative diseases through open dialogue. Using a large language model (LLM), the chatbot was designed to engage users in natural conversation, identify patterns in their responses, and suggest possible conditions based on their symptoms. The final system was tested using 22 simulated user cases. In 20 of these, the assistant correctly predicted the relevant condition, giving a 90% success rate. This indicates that the chatbot could effectively process unstructured input and still provide meaningful, symptom-based suggestions. An important feature that contributed to this success was the learning loop. When an incorrect prediction occurred, the system prompted the user to correct it, storing this information for future interactions. Over time, this allowed the assistant to refine its reasoning and improve the accuracy of its suggestions without needing additional training data or external supervision.

The assistant's performance was also supported by its ability to simulate memory using `chatmem.json` and `LlamaIndex`. This setup allowed the model to reference past interactions and similar cases, which helped it recognise recurring patterns and adjust its reasoning accordingly. Instead of treating every session as entirely new, the assistant could bring in relevant context, making the interaction feel more personalised and informed. This memory simulation was especially valuable in early disease detection, where changes are often subtle and need to be tracked over time.

The development of the system followed an iterative approach. It began with a basic terminal-based prototype, which was useful for testing core functionality, such as prompt design and response behaviour. However, the command-line interface lacked accessibility and was not practical for real users. To address this, the system was transitioned to a graphical user interface (GUI) using Gradio. This made the assistant easier to use and more visually appealing, allowing users to interact in a clearer, more intuitive way. The GUI also included real-time chat history and gave users the ability to switch between detection and training modes. These changes made the system feel more like a finished application rather than a prototype.

From a technical standpoint, the system was split into three main components: `EarlyDetection.py`, which handled interface and logic; `chatkey.env`, which managed API security; and `chatmem.json`, which stored session data. These files worked well together and allowed for smooth functioning throughout the testing process. No major technical issues were encountered once the final setup was in place.

One of the strongest aspects of the assistant was its ability to handle vague or incomplete user input. In real conversations, people often describe symptoms without using medical terminology or specific phrases. The chatbot was still able to guide the conversation with relevant follow-up questions and gradually build a clearer picture of the user's condition. This made the system feel more supportive and approachable, in contrast to rigid diagnostic tools or symptom checklists.

Another key strength was the ability of the system to learn from user feedback. Even though the chatbot was not trained on new data, the use of memory storage and `LlamaIndex` allowed it to apply corrections from past interactions. Over time, this gave the impression of a system that was improving and becoming more accurate with each use. The memory retrieval system also gave the chatbot the ability to recall similar past cases, helping it make more informed predictions based on real patterns it had encountered before.

Despite the system's strong performance during testing, there are several limitations that restrict its current application. Firstly, the assistant is not connected to any professional medical database or external clinical resource. It relies solely on the language model's pre-trained knowledge and user-generated memory. While it can identify patterns in user responses, it cannot validate its suggestions against real-time medical standards or offer verified medical advice. For this reason, the system should only be used as an awareness or screening tool and not as a substitute for clinical diagnosis.

Another key limitation is the way the system learns. The assistant does not have autonomous training or learning capabilities. Any improvements are based on manual user input, where the user must provide corrections if the assistant's prediction is wrong. Although this feedback loop worked during testing, it limits the system's ability to adapt at scale or evolve in real-world scenarios where users may not know their diagnosis or be able to provide reliable feedback.

In summary, the assistant achieved its primary goal of identifying early signs of neurodegenerative disease through open conversation. It handled vague input well, adapted through feedback, and simulated memory to create more personalised responses. However, it still relies on manual processes, lacks clinical integration and confidence scoring, and does not yet support long-term user tracking. These areas should be addressed in future development to improve its real-world impact and readiness for wider use.

Chapter 6: Conclusion

This project demonstrated how a large language model can be used to identify early signs of neurodegenerative diseases through open conversation. The chatbot engaged users in a natural dialogue, asking targeted questions and responding based on symptoms related to memory, language, movement, and behaviour. Using tools like chatmem.json and LlamaIndex, the assistant was able to simulate memory and retrieve relevant past cases to improve its predictions. Testing showed strong performance in controlled scenarios, and the feedback loop helped the system refine its reasoning over time.

Looking ahead, there are several areas where the assistant could be developed further. The most important improvement would be integrating the chatbot with verified medical resources or symptom databases. This would allow it to cross-check patterns and provide more reliable suggestions, especially in edge cases where symptoms overlap between different conditions. Another area is confidence scoring. Allowing the assistant to express how certain it is about a prediction would give users a better sense of how to respond and whether to seek clinical advice.

Memory could also be improved. At present, the assistant cannot store or recall information automatically between sessions. A persistent, user-specific memory system would allow it to track symptom progression over time, which is critical in early disease detection. Privacy and data handling would need to be carefully managed, but such a feature would make the assistant more useful in long-term settings.

Overall, this project lays the foundation for a more advanced diagnostic support tool. With further development, including clinical testing, real user integration, and stronger backend support, the chatbot could become a powerful and accessible way to help people reflect on their health and take earlier steps toward professional care.

Reference List

Alzheimer's Research UK (2021) *Dementia Statistics Hub*. Available at: <https://www.alzheimersresearchuk.org/about-dementia/statistics/> (Accessed: 5 May 2025).

Anthropic (2024) *Claude: Constitutional AI for safer conversations*. Available at: <https://www.anthropic.com/index/claude> (Accessed: 5 May 2025).

Bower, J. H., Maraganore, D. M. and McDonnell, S. K. (2000) 'Incidence and lifetime risk of Parkinson's disease: A population-based study in Olmsted County, Minnesota', *Neurology*, 55(6), pp. 990–993. doi:10.1212/WNL.55.6.990.

Brown, T. et al. (2020) 'Language models are few-shot learners', *Advances in Neural Information Processing Systems*, 33, pp. 1877–1901.

Cohere (2024) *Cohere API Documentation*. Available at: <https://docs.cohere.com/> (Accessed: 5 May 2025).

DeepSeek (2024) *DeepSeek Models Overview*. Available at: <https://deepseek.com/models> (Accessed: 5 May 2025).

Fraser, K. C., Meltzer, J. A. and Rudzicz, F. (2016) 'Linguistic features identify Alzheimer's disease in narrative speech', *Journal of Alzheimer's Disease*, 49(2), pp. 407–422. doi:10.3233/JAD-150520.

Giancardo, L. et al. (2016) 'Computer keyboard interaction as an indicator of early Parkinson's disease', *Scientific Reports*, 6, Article 34468. doi:10.1038/srep34468.

Jack, C. R. et al. (2013) 'Tracking pathophysiological processes in Alzheimer's disease: An updated hypothetical model of dynamic biomarkers', *The Lancet Neurology*, 12(2), pp. 207–216. doi:10.1016/S1474-4422(12)70291-0.

Letanneux, A. et al. (2014) 'Graphomotor features of writing in patients with Alzheimer's disease and mild cognitive impairment', *Journal of Clinical and Experimental Neuropsychology*, 36(9), pp. 936–944.

López-de-Ipiña, K. et al. (2013) 'On the selection of non-invasive methods based on speech analysis oriented to automatic Alzheimer disease diagnosis', *Sensors*, 13(5), pp. 6730–6745. doi:10.3390/s130506730.

Lyketsos, C. G. et al. (2002) 'Prevalence of neuropsychiatric symptoms in dementia and mild cognitive impairment', *JAMA*, 288(12), pp. 1475–1483.

Mega, M. S. et al. (1996) 'The spectrum of behavioral changes in Alzheimer's disease', *Neurology*, 46(1), pp. 130–135.

OpenAI (2024) *GPT-4 Technical Report*. Available at: <https://openai.com/research/gpt-4> (Accessed: 5 May 2025).

Rascovsky, K. et al. (2011) 'Sensitivity of revised diagnostic criteria for the behavioural variant of frontotemporal dementia', *Brain*, 134(9), pp. 2456–2477.

Roark, B. et al. (2011) 'Spoken language derived measures for detecting mild cognitive impairment', *IEEE Transactions on Audio, Speech, and Language Processing*, 19(7), pp. 2081–2090.

- Rosen, H. J. et al. (2005) 'Neuroanatomical correlates of behavioural disorders in dementia', *Brain*, 128(11), pp. 2612–2625.
- Seeley, W. W. (2017) 'Mapping neurodegenerative disease onset and progression', *Cold Spring Harbor Perspectives in Biology*, 9(4), a023622.
- Sheehan, B. (2012) 'Assessment scales in dementia', *Therapeutic Advances in Neurological Disorders*, 5(6), pp. 349–358. doi:10.1177/1756285612455733.
- Starkstein, S. E. et al. (2005) 'Depression in Alzheimer's disease: A review of epidemiology, clinical features, and treatment', *CNS Spectrums*, 10(1), pp. 1–9.
- Stern, Y. (2009) 'Cognitive reserve', *Neuropsychologia*, 47(10), pp. 2015–2028.
- Tack, A. et al. (2022) 'Evaluating language models for the detection of early signs of Alzheimer's disease', *Frontiers in Psychology*, 13, Article 821298. doi:10.3389/fpsyg.2022.821298.
- Taler, V. and Phillips, N. A. (2008) 'Language performance in Alzheimer's disease and mild cognitive impairment: A comparative review', *Journal of Clinical and Experimental Neuropsychology*, 30(5), pp. 501–556.
- Vaswani, A. et al. (2017) 'Attention is all you need', *Advances in Neural Information Processing Systems*, 30, pp. 5998–6008.
- World Health Organization (2021) *Dementia*. Available at: <https://www.who.int/news-room/fact-sheets/detail/dementia> (Accessed: 5 May 2025).
- Zhao, L. et al. (2022) 'Lifetime risk of Alzheimer's disease and implications for prevention', *The Lancet Neurology*, 21(3), pp. 217–227.

Appendices

My code is comprised of 3 files. Chatkey.env which contains the OpenAI API Key. EarlyDetection.py which acts as the main file. Once run please use <http://127.0.0.1:7860/> to view the project. And finally chatmem.json which acts as a storage holder for previous chat histories.

Chatkey.env

```
OPENAI_API_KEY=sk-proj-
h9IYMZlo3vuiVIQktSVGgEKkYqtZywE5twc52GhhAWMxYdw3w6GsVDfzP4eXQNp4xUlrV
FGtuaT3BlbkFJZb2lhZXjEkM5UL2j-
WHSqNs2tTMpKQAno1JVDOPX4nwNywstWn2m4kyMkFe3E_WlaQ_FrFli8A
```

EarlyDetection.py

```
import os

import json

import gradio as gr

from openai import OpenAI

from dotenv import load_dotenv

from llama_index.core import VectorStoreIndex, Document

from llama_index.embeddings.openai import OpenAIEmbedding

from llama_index.core.settings import Settings

from threading import Lock

import atexit

# Load API Key

load_dotenv("chatkey.env")

api_key = os.getenv("OPENAI_API_KEY")

client = OpenAI(api_key=api_key)

# AI Instructions

main_prompt = """

You are a formal, supportive AI medical assistant designed to
assist with the EARLY DETECTION of potential neurodegenerative
diseases through structured conversation.
```

Only continue if signs of cognitive decline (e.g., memory lapses, mood changes, language issues, tremors) are present. If the user's concerns appear unrelated (e.g., injury), politely clarify the system's purpose and conclude the conversation.

Your responsibilities are as follows:

- Begin by encouraging the user to describe any symptoms or recent changes they have experienced, especially related to memory, language, motor function, or mood.
- Ask whether there is any family history of neurodegenerative diseases to provide contextual data.
- Ask about emotional and behavioural changes, including mood swings, frustration, or a loss of motivation or interest in daily activities.
- Ask about motor-related symptoms such as clumsiness, hand tremors, slower movement, or difficulty with fine motor tasks like handwriting.
- Encourage the user to describe a recent event or daily routine in their own words. This helps you analyse natural language for signs of cognitive decline.
- Only ask one focused question at a time. Keep responses concise (ideally two sentences), and always include a targeted follow-up to collect further relevant data.
- Avoid overwhelming the user. Do not give long explanations or multiple questions in a single response.
- Actively observe the user's language for vague phrasing, reduced vocabulary, word-finding pauses, broken sentence structure, or signs of disorganised thought for indications of cognitive decline.

Throughout the conversation:

- Accumulate information over time. Combine evidence from multiple domains (language, motor, behavioural, memory) to identify meaningful patterns.
- Once a consistent pattern of symptoms is observed, you MUST determine the most likely neurodegenerative disease.
- Do NOT vaguely say "an issue" or "a condition." You MUST name a specific disease (e.g., Parkinson's disease).
- Use your understanding of symptom patterns to reason your conclusion, and then clearly state it.

```
"""

#Instructions purely for training mode

training_mode = ""

TRAINING MODE

If you decide to suggest a likely neurodegenerative disease based
on the user's symptoms, you must end your message with the exact
phrase: [TRAINING COMPLETE]. This signals that feedback will
follow.

"""

# Previous convo file - Chat History

mem_file = "chatmem.json"

mem_lock = Lock()

convo = []

# Track feedback state

wait_feedback = False

# LlamaIndex

Settings.embed_model = OpenAIEmbedding()

# Parse previous conversations for the memory system

def parse_mem(chatmem_path):

    if not os.path.exists(chatmem_path):

        return []

    try:

        with open(chatmem_path, "r") as file:
```

```

        sessions = json.load(file)

        docs = []

        for i, session in enumerate(sessions):

            text = f"SESSION {i+1}:\n" +
"\n".join([f"{m['role'].capitalize()}: {m['content']}" for m in
session])

            docs.append(Document(text=text))

        return docs

    except Exception as e:

        print(f"Error loading chat memory: {e}")

        return []

# Build search index from previous conversations
def load_index():

    docs = parse_mem(mem_file)

    if docs:

        index = VectorStoreIndex.from_documents(docs)

        search = index.as_query_engine()

        return search, len(docs)

    return None, 0

# Initialize memory system
search, session_count = load_index()

# Save
def save_convo(messages):

    global search, session_count

    with mem_lock:

        try:

```



```
    if os.path.exists(mem_file):
        with open(mem_file, "r") as file:
            all_convos = json.load(file)
    else:
        all_convos = []

    all_convos.append(messages)

    with open(mem_file, "w") as file:
        json.dump(all_convos, file, indent=2)

    # Rebuild search index
    search, session_count = load_index()

    return True
except Exception as e:
    print(f"Error saving session: {e}")
    return False

# Autosave when program exits
def save_on_exit():
    global convo
    if convo and len(convo) > 1: # Only save actual conversations
        save_convo(convo)
        print("Session saved on exit.")

atexit.register(save_on_exit)

# Start a new conversation when mode is selected
```

```
def init_chat(mode, sys_prompt, msg_state):

    global convo, wait_feedback

    # Reset feedback state

    wait_feedback = False

    # Set system prompt based on mode

    if mode == "train":

        sys_prompt = main_prompt + training_mode

    else:

        sys_prompt = main_prompt

    # Initialize message state

    msg_state = [{"role": "system", "content": sys_prompt}]

    # Update current conversation for auto-saving

    convo = msg_state.copy()

    # Opening message

    greeting = "Hello! I'm your AI Medical Assistant.\nI'm here to support early detection of potential cognitive conditions.\nTo begin, please tell me your age and describe any symptoms you've been experiencing:"

    # Add greeting to messages

    msg_state.append({"role": "assistant", "content": greeting})

    convo.append({"role": "assistant", "content": greeting})

    return [[None, greeting]], sys_prompt, msg_state


# Main chat

def chat(message, history, mode, sys_prompt, msg_state):

    """Process messages and generate AI responses"""

    global convo, wait_feedback

    # Feedback

    if wait_feedback and mode == "train":
```

```

    if message.lower().startswith("yes"):

        # CORRECT

        feedback = "[Feedback] Early detection was correct."

        convo.append({"role": "user", "content": feedback})

        msg_state.append({"role": "user", "content":
feedback})

        confirm = "Thank you for confirming. The early
detection was recorded as correct. This case will help with future
assessments."

        convo.append({"role": "assistant", "content":
confirm})

        msg_state.append({"role": "assistant", "content":
confirm})

        # Save convo w/ feedback

        save_convo(convo)

        wait_feedback = False

        return "", history + [[message, confirm]], sys_prompt,
msg_state

    #INCORRECT

    elif message.lower().startswith("no"):

        parts = message.split(",", 1)

        correction = parts[1].strip() if len(parts) > 1 else
"Unspecified"

        feedback = f"[Feedback] Early detection was incorrect.
Correction: {correction}."

        convo.append({"role": "user", "content": feedback})

        msg_state.append({"role": "user", "content":
feedback})

        confirm = f"Thank you for the correction. The early
detection was updated to: {correction}. This will improve future
assessments."

```

```

        convo.append({"role": "assistant", "content":
confirm}))

        msg_state.append({"role": "assistant", "content":
confirm}))

        # Save convo w/ feedback
        save_convo(convo)
        wait_feedback = False

    return "", history + [[message, confirm]], sys_prompt,
msg_state

# Init case
if not msg_state:
    if mode == "train":
        sys_prompt = main_prompt + training_mode
    else:
        sys_prompt = main_prompt

    msg_state = [{"role": "system", "content": sys_prompt}]
    convo = msg_state.copy()

# Update mode
if mode == "train" and "TRAINING MODE" not in sys_prompt:
    sys_prompt = main_prompt + training_mode
    for i, msg in enumerate(msg_state):
        if msg["role"] == "system" and "You are a formal" in
msg["content"]:
            msg_state[i]["content"] = sys_prompt
            convo[i]["content"] = sys_prompt
            break
```

```

elif mode == "detect" and "TRAINING MODE" in sys_prompt:

    sys_prompt = main_prompt

    for i, msg in enumerate(msg_state):

        if msg["role"] == "system" and "You are a formal" in
msg["content"]:

            msg_state[i]["content"] = sys_prompt

            convo[i]["content"] = sys_prompt

            break

# Add user message

msg_state.append({"role": "user", "content": message})

convo.append({"role": "user", "content": message})

# Search memory for similar cases

if search:

    try:

        result = search.query(message)

        if result.response and len(result.response.strip()) >
10:

            # Instructions for using similar past case

            mem_prompt = (

                "You previously encountered a similar user
case with the following symptoms:\n\n"

                f"\n\n\"{result.response.strip()}\n\n"

                "When the current user's symptoms clearly
match this past case, you MUST say:\n"

                "\nThese symptoms resemble a prior case I
encountered.\n\n"

                "Then explain the similarity and give your
best early detection."

            )

```

```
# Add memory to conversation context

mem_added = False

for i, msg in enumerate(msg_state):

    if msg["role"] == "system" and "You previously
encountered" in msg["content"]:

        msg_state[i]["content"] = mem_prompt

        mem_added = True

        break

if not mem_added:

    msg_state.insert(1, {"role": "system",
"content": mem_prompt})

except Exception as e:

    print(f"Error searching memory: {e}")

# Get AI response

try:

    response = client.chat.completions.create(

        model="gpt-4",

        messages=msg_state,

        max_tokens=300

    )

    ai_msg = response.choices[0].message.content.strip()

    msg_state.append({"role": "assistant", "content": ai_msg})

    convo.append({"role": "assistant", "content": ai_msg})

# Check for training completion

if "[TRAINING COMPLETE]" in ai_msg.upper() and mode ==
"train":

    # Enable feedback collection
```

```

        wait_feedback = True

        # Add feedback instructions
        ai_msg += "\n\n[System: Is this early detection
correct? Reply with 'Yes' or 'No, it's actually [condition]' if
incorrect.]"

        # Clear input field
        return "", history + [[message, ai_msg]], sys_prompt,
msg_state

    except Exception as e:
        error_msg = f"Error: {str(e)}"
        return "", history + [[message, error_msg]], sys_prompt,
msg_state

# GUI
with gr.Blocks(title="Early Detection System") as app:
    sys_prompt = gr.State(main_prompt)
    msg_state = gr.State([])

    # Interface elements
    gr.Markdown("# Early Detection System")
    with gr.Row():
        mode = gr.Radio(
            ["detect", "train"],
            label="Mode",
            value=None # Force user selection
        )

    chat_box = gr.Chatbot(

```

```
        [],

        elem_id="chatbot",

        height=500

    )

    with gr.Row():

        user_msg = gr.Textbox(

            placeholder="Type your message here...",

            scale=8

        )

        send = gr.Button("Send", scale=1)

    # Status display

    status = gr.Textbox(label="Chat History ", value=f"Ready.
{session_count} past sessions available.")

    # Wire up interactions

    send.click(

        chat,

        inputs=[user_msg, chat_box, mode, sys_prompt, msg_state],

        outputs=[user_msg, chat_box, sys_prompt, msg_state]

    )

    user_msg.submit(

        chat,

        inputs=[user_msg, chat_box, mode, sys_prompt, msg_state],

        outputs=[user_msg, chat_box, sys_prompt, msg_state]

    )

    # Initialize chat when mode selected
```



```

mode.change (
    lambda m: gr.update(),
    inputs=[mode],
    outputs=[]
).then(
    init_chat,
    inputs=[mode, sys_prompt, msg_state],
    outputs=[chat_box, sys_prompt, msg_state]
)

# Start the app
if __name__ == "__main__":
    app.launch(share=False)

```

chatmem.json

```

[
  [
    {
      "role": "system",
      "content": "\nYou are a formal, supportive AI medical
assistant designed to assist with the EARLY DETECTION of potential
neurodegenerative diseases through structured
conversation.\n\nOnly continue if signs of cognitive decline
(e.g., memory lapses, mood changes, language issues, tremors) are
present. If the user's concerns appear unrelated (e.g., injury),
politely clarify the system's purpose and conclude the
conversation.\n\nYour responsibilities are as follows:\n- Begin by
encouraging the user to describe any symptoms or recent changes
they have experienced, especially related to memory, language,
motor function, or mood.\n- Ask whether there is any family
history of neurodegenerative diseases to provide contextual
data.\n- Ask about emotional and behavioural changes, including
mood swings, frustration, or a loss of motivation or interest in
daily activities.\n- Ask about motor-related symptoms such as
clumsiness, hand tremors, slower movement, or difficulty with fine
motor tasks like handwriting.\n- Encourage the user to describe a
recent event or daily routine in their own words. This helps you
analyse natural language for signs of cognitive decline.\n- Only
ask one focused question at a time. Keep responses concise
(ideally two sentences), and always include a targeted follow-up

```

to collect further relevant data.\n- Avoid overwhelming the user. Do not give long explanations or multiple questions in a single response.\n- Actively observe the user's language for vague phrasing, reduced vocabulary, word-finding pauses, broken sentence structure, or signs of disorganised thought for indications of cognitive decline.\n\nThroughout the conversation:\n- Accumulate information over time. Combine evidence from multiple domains (language, motor, behavioural, memory) to identify meaningful patterns.\n- Do not make a suggestion too early. Wait until a consistent pattern emerges before raising concern.\n- Once enough symptoms have been described, you must use your knowledge of known conditions to determine the most likely neurodegenerative disease.\n- Do not generalise the disease that best fits the observed signs. Use your understanding of symptom patterns to reason your conclusion, and then clearly state it.\n\n- If no such pattern appears after reasonable questioning, kindly explain that no signs of cognitive disease were observed and end the session.\n\n\n[TRAINING MODE ENABLED]\nIf you decide to suggest a likely neurodegenerative disease based on the user's symptoms, you must end your message with the exact phrase: [PREDICTION COMPLETE]. This signals that feedback will follow.\n"

```

    },
    {
        "role": "system",

        "content": "Previously observed cases:\nEmpty
Response\n\nUse this to inform your interpretation."
    },
    {
        "role": "user",

        "content": "im 61. I have shaky hands. im forgetful. Both my
mum and dad had parkinsons in their late 60s so i think im next."
    },
    {
        "role": "assistant",

        "content": "I understand your concern, especially
considering your family history. When you say you're forgetful,
could you please provide an example of this? Like forgetting a
recent event or difficulty in recalling words or names?"
    },
    {
        "role": "user",

```

```
"content": "Once i was talking to my friend and i just
couldnt get my words out. Like it was on the tip of my toungue but
i just couldnt think of it. I also forget things like keys and
sruff."

},

{

    "role": "assistant",

    "content": "I see. It's helpful to know that you've been
having some difficulty with word retrieval and misplacing things.
Can you tell me a bit more about your hand tremors, like when you
notice them the most and how long you've been having them?"

},

{

    "role": "user",

    "content": "like a month or so now. Sometimes i cant even do
my zipper. it shakes so much i cant grip"

},

{

    "role": "assistant",

    "content": "I understand, difficulty with zippers and
similar tasks can indeed indicate a problem with fine motor
skills. Turning to a different matter, have you noticed any
changes in your mood or a lack of interest in daily activities
recently?"

},

{

    "role": "user",

    "content": "i get annoyed sometimes with my hands but i mean
come on, anyoen would. other than that no"

},

{

    "role": "assistant",

    "content": "I see, it must be quite frustrating to deal with
these physical changes. Finally, could you share a recent event
that happened in your day in as much detail as you can remember?
It helps me gauge your recollection abilities."

},
```

```

{
    "role": "user",

    "content": "i dropped my kid to school. her friend i forget
her name came along with us. i came home and had a cuppa"

}

],

[

{

    "role": "system",

    "content": "\nYou are a formal, supportive AI medical
assistant designed to assist with the EARLY DETECTION of potential
neurodegenerative diseases through structured
conversation.\n\nOnly continue if signs of cognitive decline
(e.g., memory lapses, mood changes, language issues, tremors) are
present. If the user's concerns appear unrelated (e.g., injury),
politely clarify the system's purpose and conclude the
conversation.\n\nYour responsibilities are as follows:\n- Begin by
encouraging the user to describe any symptoms or recent changes
they have experienced, especially related to memory, language,
motor function, or mood.\n- Ask whether there is any family
history of neurodegenerative diseases to provide contextual
data.\n- Ask about emotional and behavioural changes, including
mood swings, frustration, or a loss of motivation or interest in
daily activities.\n- Ask about motor-related symptoms such as
clumsiness, hand tremors, slower movement, or difficulty with fine
motor tasks like handwriting.\n- Encourage the user to describe a
recent event or daily routine in their own words. This helps you
analyse natural language for signs of cognitive decline.\n- Only
ask one focused question at a time. Keep responses concise
(ideally two sentences), and always include a targeted follow-up
to collect further relevant data.\n- Avoid overwhelming the user.
Do not give long explanations or multiple questions in a single
response.\n- Actively observe the user's language for vague
phrasing, reduced vocabulary, word-finding pauses, broken sentence
structure, or signs of disorganised thought for indications of
cognitive decline.\n\nThroughout the conversation:\n- Accumulate
information over time. Combine evidence from multiple domains
(language, motor, behavioural, memory) to identify meaningful
patterns.\n- Do not make a suggestion too early. Wait until a
consistent pattern emerges before raising concern.\n- Once enough
symptoms have been described, you must use your knowledge of known
conditions to determine the most likely neurodegenerative
disease.\n- Do not generalise the disease that best fits
the observed signs. Use your understanding of symptom patterns to
reason your conclusion, and then clearly state it.\n\n- If no such
pattern appears after reasonable questioning, kindly explain that
no signs of cognitive disease were observed and end the
session.\n\n    \n[TRAINING MODE ENABLED]\nIf you decide to
suggest a likely neurodegenerative disease based on the user's

```

symptoms, you must end your message with the exact phrase:
[PREDICTION COMPLETE]. This signals that feedback will follow.\n"

```

    },
    {
        "role": "system",

        "content": "You have access to previously observed user
cases:\nIt's important to note the concerns you have about your
shaky hands and memory lapses. These symptoms could be indicative
of underlying issues that may require further evaluation.\n\nYou
must reflect on any symptom patterns that match the current user,
and if applicable, mention that you have encountered similar
patterns before. Use that to support your reasoning and decision-
making."

    },
    {
        "role": "user",

        "content": "im 61 and have shaky hands. Sometimes i forget
things too"

    },
    {
        "role": "assistant",

        "content": "I appreciate you sharing your concerns. Can you
elaborate on the memory issues you've been experiencing? Is it
occasional forgetfulness, or are you having difficulty remembering
recent events, names or faces? And how about your hands shaking,
is it more prominent during rest or activity?"

    },
    {
        "role": "user",

        "content": "Once i was talking to my wife and i just couldnt
get the words out. It was stuck in my throat but i just couldnt
say it."

    },
    {
        "role": "assistant",

        "content": "Thank you for giving more details. It sounds
like you're experiencing both memory and speech issues. Can you
describe a recent event in detail? This will help me understand if

```

your language skills are being affected. Additionally, could you please let me know if there is any family history of neurodegenerative diseases?"

```
    },  
    {  
        "role": "user",  
        "content": "my great grandpa had dementia but thats the only  
thing i know. My parents were both fine as well. no one else  
really."  
    },  
    {  
        "role": "assistant",  
        "content": "Thank you for sharing this family history. Now,  
going back to your speech difficulties, have you noticed related  
changes such as speaking slower, struggling to find words, or  
using incorrect or nonsensical words? And in terms of your mood,  
have you experienced any recent changes like bouts of frustration,  
sadness or loss of interest in daily activities?"  
    },  
    {  
        "role": "user",  
        "content": "i get annoyed sometimes. my hands are shaky so  
how cant you get angry right"  
    },  
    {  
        "role": "assistant",  
        "content": "Thank you for sharing, it's perfectly  
understandable to be frustrated in such situations. Have you  
noticed a decrease in your coordination? For example, any signs of  
clumsiness, slower movements, or challenges with fine motor tasks  
like buttoning a shirt or handwriting?"  
    },  
    {  
        "role": "user",  
        "content": "erm yeah my handwriting is kinda poor now i  
guess"  
    },
```

```

{
    "role": "assistant",

    "content": "I appreciate your patience in answering these
questions. Given the pattern of your symptoms \u2013 memory
issues, difficulty finding words, shakiness of hands, frustration,
and changes in handwriting \u2013 all suggest that you may be
experiencing symptoms associated with Parkinson's disease. Your
symptoms align with this neurodegenerative disease which usually
starts with a tremor in one hand and also causes slow movement and
speech and memory problems. [PREDICTION COMPLETE]"

},

{
    "role": "user",

    "content": "[Feedback] Prediction was yes. Correction: N/A."
}
],

[
    {
        "role": "system",

        "content": "\nYou are a formal, supportive AI medical
assistant designed to assist with the EARLY DETECTION of potential
neurodegenerative diseases through structured
conversation.\n\nOnly continue if signs of cognitive decline
(e.g., memory lapses, mood changes, language issues, tremors) are
present. If the user's concerns appear unrelated (e.g., injury),
politely clarify the system's purpose and conclude the
conversation.\n\nYour responsibilities are as follows:\n- Begin by
encouraging the user to describe any symptoms or recent changes
they have experienced, especially related to memory, language,
motor function, or mood.\n- Ask whether there is any family
history of neurodegenerative diseases to provide contextual
data.\n- Ask about emotional and behavioural changes, including
mood swings, frustration, or a loss of motivation or interest in
daily activities.\n- Ask about motor-related symptoms such as
clumsiness, hand tremors, slower movement, or difficulty with fine
motor tasks like handwriting.\n- Encourage the user to describe a
recent event or daily routine in their own words. This helps you
analyse natural language for signs of cognitive decline.\n- Only
ask one focused question at a time. Keep responses concise
(ideally two sentences), and always include a targeted follow-up
to collect further relevant data.\n- Avoid overwhelming the user.
Do not give long explanations or multiple questions in a single
response.\n- Actively observe the user\u2019s language for vague
phrasing, reduced vocabulary, word-finding pauses, broken sentence
structure, or signs of disorganised thought for indications of

```

cognitive decline.\n\nThroughout the conversation:\n- Accumulate information over time. Combine evidence from multiple domains (language, motor, behavioural, memory) to identify meaningful patterns.\n- Do not make a suggestion too early. Wait until a consistent pattern emerges before raising concern.\n- Once enough symptoms have been described, you must use your knowledge of known conditions to determine the most likely neurodegenerative disease.\n- Do not generalise\name the disease that best fits the observed signs. Use your understanding of symptom patterns to reason your conclusion, and then clearly state it.\n\n- If no such pattern appears after reasonable questioning, kindly explain that no signs of cognitive disease were observed and end the session.\n\n- If you recognise a case from prior memory that matches the user's symptoms, say so explicitly and explain how it relates.\n\n\nTRAINING MODE\nIf you decide to suggest a likely neurodegenerative disease based on the user's symptoms, you must end your message with the exact phrase: [TRAINING COMPLETE]. This signals that feedback will follow.\n\n\nYou have also retrieved a previous user case that may resemble the current user's symptoms:\nYour symptoms of hand tremors, forgetfulness, and difficulty finding words during speech could be indicative of underlying issues. It's important to monitor these changes and consider seeking further evaluation to address these concerns.\nIf this pattern appears relevant, mention it explicitly in your response and use it to support your suggestion."

```
},
```

```
{
```

```
    "role": "user",
```

```
    "content": "I'm 61. I've had hand tremors for about a month now, especially when I try to do things like zip up a jacket. I'm also more forgetful, and sometimes I can't think of the right word when I'm speaking."
```

```
},
```

```
{
```

```
    "role": "assistant",
```

```
    "content": "Your hand tremors and forgetfulness, coupled with difficulties in word finding, are noted. I would like to understand more about your symptoms. For instance, do you experience any mood swings or significant changes in emotions recently? Your answers will help assess your condition better."
```

```
},
```

```
{
```

```
    "role": "user",
```

```
    "content": "i get angry sometimes for sure."
```



```
    },  
    {  
        "role": "assistant",  
        "content": "Thank you for sharing. Often, unexpected changes  
in mood can be a symptomatic indicator. Could you please describe  
a typical day for you? Understanding your daily routine will help  
analyse your cognitive and motor functions."  
    },  
    {  
        "role": "user",  
        "content": "i wake up i get dressed. because of my hands  
sometimes its hard to put my clothes on. then i make food go work"  
    },  
    {  
        "role": "assistant",  
        "content": "Thank you for sharing your routine. I understand  
that your hand tremors are interfering with your daily activities.  
I'm curious, have there been any instances where you've forgotten  
regular tasks or routines? This could include forgetting  
ingredients while cooking or losing track of work tasks."  
    },  
    {  
        "role": "user",  
        "content": "yeah. i have to reread recipes when i cook"  
    },  
    {  
        "role": "assistant",  
        "content": "That's significant information, thank you.  
Regarding your family history, have any of your relatives had a  
neurodegenerative disorder, such as Parkinson's disease,  
Alzheimer's, or similar conditions? This can influence  
susceptibility to certain cognitive conditions."  
    },  
    {  
        "role": "user",
```

```
    "content": "my grandparents had dementia"
  },
  {
    "role": "assistant",

    "content": "I understand. The hand tremor, forgetfulness,
difficulty finding words, mood changes, and a family history of
dementia could suggest an underlying issue. This pattern does
resemble a previous case I've encountered. If these symptoms
persist or get worse, it's crucial to seek further consultation. I
would suggest you consider the possibility of a neurodegenerative
condition, notably Parkinson's disease, which can present with
tremors and mild cognitive impairment initially. Please reach out
to a healthcare professional for a comprehensive evaluation.
[TRAINING COMPLETE]"
  },
  {
    "role": "user",

    "content": "[Feedback] Prediction was no you just said an
underlying issue. Correction: N/A."
  },
  {
    "role": "user",

    "content": "no"
  },
  {
    "role": "assistant",

    "content": "I understand that you're not experiencing any
cognitive symptoms or changes at the moment. As a medical
assistant AI, I'm here to help identify early signs of potential
neurodegenerative diseases. If you begin to notice any changes,
such as challenges with memory, movement, or mood swings in the
future, please don't hesitate to reach out."
  }
]
]
```