AI Based Assistance for People with Alzheimer's Disease

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Abstract—This study underscores the utilization of AI-based technologies to support individuals affected by Alzheimer's Disease (AD) and their caregivers. The following presents a succinct overview of research papers that tackle the obstacles confronted by AD patients, along with innovative AI solutions. Explored topics encompass the creation of mobile applications, deployment of deep learning algorithms, integration of voiceactivated technologies, and application of systems biology approaches. These technological interventions provide a spectrum of features including memory-boosting games, medication reminders, location tracking, cognitive exercises, and emotional support. Through harnessing AI advancements, these solutions aspire to augment patient independence, aid in daily activities, enhance communication, and contribute to overall well-being. Key findings underscore the importance of user-friendly interfaces, personalized support, and seamless integration with existing healthcare systems. Additionally, privacy, security, and effective integration with clinical data emerge as crucial considerations. Ongoing research in this domain holds the promise of further advancements to positively impact the lives of those affected by

Index Terms—Large Language Models, Long short term memory, Machine learning, Prompt Engineering, Alzheimer's Disease, Congnitive activites.

I. INTRODUCTION

This project report provides a brief literature survey on AI-based assistive technologies for Alzheimer's Disease (AD). The survey explores innovative solutions aimed at improving the quality of life for AD patients and supporting their caregivers. The survey encompasses mobile applications, AI systems, voice-activated technologies, robot assistants, and chatbots. Mobile applications utilizing AI features have been developed to enhance memory, medication management, and recognition of people. These apps also offer features such as location tracking for patient safety and caregiver monitoring. AI systems based on deep learning algorithms monitor patient activities, track eating and hydration habits, and provide valuable insights for remote caregivers. Voiceactivated consumer technologies assist AD patients with daily activities, emotional support, and social engagement, promoting understanding and independence.

A system biology approach, integrating clinical and multiomics data with AI models, enables early detection, personalized treatment plans, and specialized medical care. AI-based robot assistance systems utilize sensors, cameras, and machine learning algorithms to aid with daily activities, personalized care, and continuous monitoring. Chatbot-based solutions provide companionship, cognitive rehabilitation, evaluation of daily activities, and medication support. These technologies offer promising avenues for addressing the unique challenges of Alzheimer's Disease.

In summary, AI-based assistive technologies exhibit significant potential for enhancing the lives of individuals affected by Alzheimer's Disease (AD) and providing support to caregivers. This survey underscores the promising role of mobile apps, AI systems, voice-activated technologies, robot assistants, and chatbots in effectively addressing the distinctive challenges associated with Alzheimer's Disease.

II. LITERATURE SURVEY

Currently there are few AI based approaches that help Alzheimer Disease patients and their caregivers to harmonize, cope with memory loss and help the AD patients to live an independent life. Given below are the summaries of few research papers that are studied and analysed the problems faced by both the AD patients and the caregivers.

A. Alzheimer's disease assistance for patients and caregivers

The paper [1] discusses an AI-based Android application named "AlzCure" that has features to help Alzheimer's patients and their caregivers. However, the paper does not discuss the effectiveness of the application in improving the quality of life of Alzheimer's patients or the challenges faced during the development of the application.

B. Deep learning to help Alzheimer patient's activities

The paper [2] discusses an AI system based on deep learning algorithms that recognizes human activity through video to keep track of when the patient eats or hydrates themselves and in what quantity they do the same. However, the paper does not discuss the effectiveness of the system in improving the quality of life of Alzheimer's patients or the challenges faced during the development of the system.

C. Voice activated reminder assistant

The paper [3] presents a voice-activated consumer technology that reminds Alzheimer's patients about their day-to-day activities and helps them cope up with emotional stress.

However, the paper does not discuss the effectiveness of the application in improving the quality of life of Alzheimer's patients or the challenges faced during the development of the application

D. Robot based AI assistant

The paper [4] proposes an AI-based robot assistance system for Alzheimer's patients that assists them in performing daily activities. However, the paper does not discuss the effectiveness of the system in improving the quality of life of Alzheimer's patients or the challenges faced during the development of the system.

E. AI-based medical assistant

The paper [5] reviews an AI-based medical assistant that is used to solve the problem of assistive technology for people with MCI and dementia. However, the paper does not discuss the effectiveness of the medical assistant in improving the quality of life of Alzheimer's patients or the challenges faced during the development of the medical assistant.

F. Intelligent cognition assistant

The paper [6] presents an open-source intelligent cognition assistant (iCA) to improve the quality of life of people with dementia. However, the paper does not discuss the effectiveness of the iCA in improving the quality of life of Alzheimer's patients or the challenges faced during the development of the iCA.

G. Tele-operated companionship

The paper [7] proposes a user-centered tele-operated assistive robot that mainly focuses on companionship. However, the paper does not discuss the effectiveness of the robot in improving the quality of life of Alzheimer's patients or the challenges faced during the development of the robot.

H. Chatbots for Alzheimer's patient's

The paper [8] conducts a systematic review on the functions of various chatbots and essentially studies the kind of support each provides to people suffering from dementia. However, the paper does not discuss the effectiveness of the chatbots in improving the quality of life of Alzheimer's patients or the challenges faced during the development of the chatbots.

III. METHODOLOGY

A. Data Generation Process

We generated synthetic data for patient emotions over time using Python. The process involved several steps:

- Setting up the parameters: We initialized variables such as the number of records (number_of_records) and created empty lists to store the data.
- Looping through records: We iterated over the specified number of records and generated random values for day, month, hour, minutes, and seconds to create timestamps (date_time). We also randomly assigned responses (response) as either 0 or 1.

 Calculating emotions: We calculated emotions (emotion) based on the formula:

$$emotion = \left(\frac{hour}{100}\right) \times \text{emotion_factor} + \left(\frac{sec}{100}\right)$$

where emotion_factor is a randomly chosen value between 1 and 5. If the calculated emotion exceeded 5, we capped it at 5.

- Determining outcomes: We determined outcomes (outcome) based on the calculated emotions. If the emotion was less than or equal to 1.5 or between 2 and 3, the outcome was set to 0.0. If the emotion was between 3.5 and 4.5, the outcome was randomly chosen as 0 or 1. For emotions greater than 4.5, the outcome was set to 1.0.
- Storing data: We stored the generated data in lists and then converted it into a pandas DataFrame. Finally, we sorted the DataFrame based on the timestamps.

B. Outcome Determination

The outcome (outcome) for each patient is determined based on their calculated emotion. We use the following rules:

- If emotion ≤ 1.5 or emotion > 2, the outcome is set to 0.0.
- If 3.5 ≤ emotion ≤ 4.5, the outcome is randomly chosen as 0 or 1.
- If emotion > 4.5, the outcome is set to 1.0.

TABLE I SAMPLE OF GENERATED DATA

Date_Time	Response	Emotion	Outcome
03/15/24 1:03:56	0.0	1.03056	0.0
03/15/24 2:01:17	1.0	2.0117	0.0
03/15/24 3:05:29	0.0	3.0529	0.0
03/15/24 4:02:42	1.0	4.0242	1.0
03/15/24 5:00:56	0.0	5.0056	1.0

C. LSTM Architecture

The LSTM architecture utilized in your project comprises:

- **Input Layer:** Receives sequential data representing various features relevant to the emotional state of Alzheimer's patients over time.
- LSTM Layer: Serves as the core component of the model, capable of learning and capturing complex temporal patterns in the input data. Analyzes the sequential data to understand how patient emotions evolve over time.
- Dense Layers: Further process the extracted features to make predictions about patient emotions. The first dense layer introduces non-linearity to capture intricate relationships, while the second dense layer produces final emotion predictions.
- Compilation: The model is compiled with appropriate loss and optimization functions tailored to minimize prediction errors in estimating patient emotions over time.
- Training: During training, the model learns from sequential data to improve its ability to predict patient

emotions. Adjusts its parameters to better capture underlying patterns and dynamics of emotional fluctuations in Alzheimer's patients.

D. Block Diagram

The block diagram illustrates the flow of data through the LSTM architecture relative to our project:

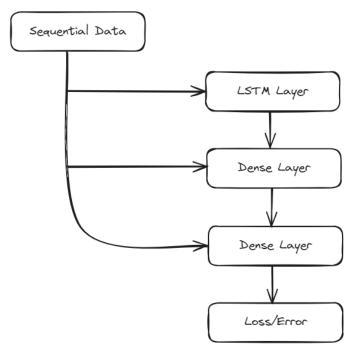


Fig. 1. Block Diagram of LSTM Architecture for Alzheimer's Care Project

In the block diagram:

- The sequential data represents various inputs related to patient interactions, environmental conditions, and temporal factors.
- The LSTM layer analyzes this sequential data to capture the temporal dynamics of patient emotions, leveraging its ability to retain long-term dependencies.
- The dense layers process the LSTM outputs to generate predictions about patient emotions.
- The loss/error calculation quantifies the model's performance in estimating patient emotions over time.

Overall, the LSTM architecture, adapted to the context of Alzheimer's care, enables your project to predict and understand the emotional trajectories of patients, providing valuable insights for personalized assistance and support.

E. Brain games

Periodically, brain games are proposed that match patient preferences and abilities. Game difficulty and frequency are adjusted based on engagement and performance. The conversational AI may also generate cognitive game prompts for the patient. The patient plays the cognitive games, and their progress is stored in the database.

The model retraining module periodically retrains the conversational AI and adaptive cognitive game prompters using new data from the database. The logging and monitoring module logs all system activity and monitors key metrics.

Algorithm 1 Data Generation and LSTM Model Training for game and meal reminders

Require: Import necessary packages

function GenerateDataAndTrainModel

Initialize number of records, date-time list, response list, emotion list, outcome list

Create an empty list to store records

for i in range(number of records) do

Generate random day, month, hour, minutes, and seconds

Create date-time string in the format "month/day/24 hour:minutes:seconds"

Generate response as a random float (0.0 or 1.0)

Generate emotion using a formula involving hour, seconds, and a random factor

Clip emotion to be within the range [1.0, 5.0]

Determine outcome based on the value of emotion Append record [date-time, response, emotion, outcome] to the list

end for

Create a DataFrame from the list with columns ["date_time", "response", "emotion", "outcome"]

Convert "date_time" column to datetime and set it as the index

Sort the DataFrame by the index in ascending order Plot the first 300 records of the emotion over time

Create a function DF_TO_X_Y to convert DataFrame to input-output pairs

Apply DF_TO_X_Y on the "emotion" column with a specified window size

Split the data into training, validation, and test sets

Create a Sequential model with LSTM layers for training

Compile the model with Mean Squared Error loss and Adam optimizer

Train the model on the training data, using validation data and ModelCheckpoint

Load the trained model from the saved directory

Make predictions on the training set and compare with actual values

end function

F. Memory reminiscing

Patient-specific memories are accessed from the database and incorporated into conversation to promote reminiscing and emotional connection.

The provided **Algorithm 2** generates synthetic data for training an LSTM model to predict emotional responses over time. It initializes various lists to store date-time, response, emotion, and outcome records, with each record being

generated through a combination of random factors. After creating a DataFrame from these records, the algorithm plots the first 300 emotion records over time. It then transforms the DataFrame into input-output pairs with a specified window size and splits the data into training, validation, and test sets. A Sequential model with LSTM layers is constructed, compiled, and trained on the training data using the Adam optimizer and Mean Squared Error loss. The trained model is loaded, and predictions are made on the training set to evaluate its performance in predicting emotional responses based on the generated synthetic data.

G. Continuous learning

Patient interactions and feedback are used to improve conversation models, personalize experiences, and refine brain games and memory prompts

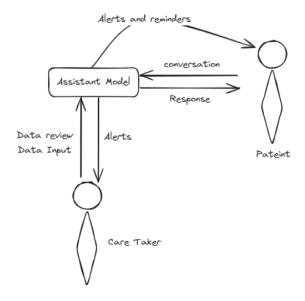


Fig. 2. Block Diagram of the system

IV. RESULTS

A. Threshold value not satisfying

sentiment value is 0.8
Sentiment is not favorable for playing the game.

Fig. 3. Not favourable Sentiment

B. Threshold value satisfying



Fig. 4. Game Interface



Fig. 5. Game Won

V. LIMITATIONS

While the AI-based assistive technologies discussed in this study demonstrate considerable potential, it is crucial to acknowledge and address their inherent limitations. The accuracy and reliability of speech recognition, emotion detection, and cognitive game adaptation algorithms may pose challenges, necessitating further refinement and validation. Additionally, the integration of diverse data sources, including clinical data, patient records, and environmental sensors, to create comprehensive and personalized AI models presents a

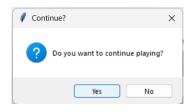


Fig. 6. Continue Playing?



Fig. 7. Game Lost

significant hurdle. Ethical considerations and privacy concerns surrounding the collection, storage, and usage of sensitive patient data must be addressed through robust data protection measures. Moreover, potential barriers to adoption, such as technology literacy among older adults and caregivers, as well as the accessibility and affordability of these AI-based solutions, cannot be overlooked. Extensive testing, validation, and regulatory approval processes are imperative to ensure the safety and efficacy of these technologies before widespread deployment. Furthermore, the current literature review may be limited in scope, and more comprehensive studies are needed to evaluate the real-world impact of these technologies on Alzheimer's patients and caregivers.

VI. CONCLUSION

In conclusion, the integration of AI technology in assisting Alzheimer's patients represents a significant step forward in the field of dementia care. By harnessing the power of artificial intelligence, we have the opportunity to profoundly impact the lives of both patients and caregivers.

One of the most compelling aspects of this approach is its potential to offer personalized support. Alzheimer's disease manifests differently in each individual, and traditional care methods often struggle to address this variability. However, with AI-driven systems capable of adapting to the unique needs and preferences of each patient, we can provide tailored assistance that enhances independence and dignity.

Moreover, by incorporating cognitive stimulation into daily routines, these systems offer more than just practical assistance—they provide opportunities for meaningful engagement and mental stimulation. By prompting memory games and interactive activities, the AI assistant encourages cognitive function and memory retention, potentially slowing the progression of cognitive decline.

Additionally, the routine management features of these systems can significantly alleviate caregiver burden. Automated reminders for meal times and daily activities help establish a structured routine, reducing anxiety and confusion for both patients and caregivers. This, in turn, allows caregivers to focus more on providing emotional support and meaningful interactions with their loved ones, rather than being overwhelmed by the logistics of daily care.

Furthermore, the data collected from patient interactions can offer valuable insights into disease progression and treatment effectiveness. By analyzing patterns and trends in patient behavior, researchers and healthcare professionals can gain a deeper understanding of Alzheimer's disease and develop more effective interventions.

As we continue to refine and expand upon these technologies, we move closer to a future where individuals living with Alzheimer's disease can lead fulfilling and dignified lives, supported by intelligent and empathetic AI systems. While there are still challenges to overcome and ethical considerations to address, the potential for positive impact

is undeniable. With ongoing research, collaboration, and innovation, we can harness the full potential of AI to improve the lives of Alzheimer's patients and their caregivers.

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