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Artificial Intelligence Based Alzheimer's Disease Detection and Treatment Recommendation System

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Abstract: **-** The significance of the use of Artificial Intelligence techniques towards early diagnosis, detection, and treatment of Alzheimer's disease (AD) is highlighted in this research work. This work proposes an inclusive AI system that combines several significant aspects: MRI analysis for detecting and staging early on the disease, emotion recognition and response analysis, risk assessment, and memory therapy sessions. The system employs advanced deep learning algorithms to read MRIs to diagnose structural changes within the most vital regions of the brain including the hippocampus, temporal lobe, frontal lobe parietal lobe. The system also has emotion recognition abilities via facial expression analysis and voice data analysis provides enough answers to ensure emotional well-being among the patients. The analysis is done by machine learning. algorithms that are exposed to the handling of data from various Data sources like demographic data, medical history, cognitive test scores, and lifestyle traits. The system also has specialized memory treatment exercises such as the memorization sequence games and picture recall to enhance cognitive skills Cities. In prediction cases on a patient's condition, suitable treatment recommendations and therapy adjustments are provided by the system. Secondly, the system contains elaborate tracking and reporting features that allow healthcare professionals to monitor patient improvement and adjust interventions accordingly. The study highlights the vast advantages and potential achieved through employing this AI-based diagnostic system, in addition to the challenges and potential disruptions which can affect its successful implementation in healthcare environments. The potential for future enhancement of the system's functionality is also addressed in this study.

Keywords: *Alzheimer's disease, early detection, emotion recognition, memory therapy, MRI analysis*.

1. Introduction

AD represents the leading cause of dementia in elderly adults worldwide since it impacts more than 55 million patients who develop this condition and occurs in 60%–70% of dementia cases. 55 million individuals globally [1]. AD manifests as a progressive nerve system degeneration that produces beta-amyloid plaques together with neurofibrillary tangles during its initial stages focusing damage on the hippocampus and entorhinal cortex while later affecting wider areas of the cortex. The pathological development sets off a chain of detrimental processes affecting brain cells that lead to synaptic loss and finally results in cellular breakdown and shows clinical symptoms of memory impairment and cognitive deterioration along with behavioral changes as well as diminished functional independence [2]. The disease-related socioeconomic burden of AD causes extensive emotional distress and heavy financial costs which affect both healthcare organizations and worldwide economies and their patients and caregivers. Currently available epidemiological statistics show that 6.5 million Americans have AD with separate population counts of 2.41 million people in the 75-84 age range and 2.31 million people who are 85 years old or above. The growing elderly population worldwide demands immediate attention because experts anticipate a significant increase in AD cases to 2050.

The precise and prompt diagnosis of AD proves difficult to accomplish regarding the extensive neuroimaging and biomarker research conducted during the previous decade. Medical examinations together with cognitive tests and structural imaging procedures currently lack the ability to detect AD until after extensive neurodegeneration occurs which typically starts several years before clinical manifestations appear. The confidence levels of clinical diagnosis stand between 60-70 according to post-mortem neuropathological assessments which demonstrate a problem with present-day diagnostic tools. Early therapeutic intervention becomes limited because other neurodegenerative disorders in patients share quite similar characteristics with AD [3].

The brain regions targeted by AD develop symptoms successively beginning with memory-centered hippocampus and entorhinal cortex until the condition spreads to the temporal lobes for language processing followed by parietal lobes for spatial cognition and frontal lobes for executive capacity. Medical professionals in clinical practice must resolve two major diagnostic issues which include determining if a patient suffers from AD followed by identifying the disease's current stage of progression. Stage specific treatment plans allow healthcare providers to develop suitable treatments once they accurately detect and stage AD [4].

The diagnostic problems together with the intricate multiple character of AD progression call for fresh approaches in both detection and management of the disease. The disease detection capabilities of Artificial Intelligence (AI) use its recognition of difficult-to-detect patterns among different data types that standard assessment tools cannot detect [5]. Disciplines under Machine Learning (ML) and Deep Learning (DL) technology demonstrate powerful abilities for neuroimaging data examination while offering discovery of fresh biomarkers and improved AD progression predictions and enhanced clinical decisions across multiple AD treatment areas.[6] The computer system uses multiple data stream analysis to simultaneously process neuroimaging results alongside genetic information and cognitive scoring data alongside clinical measurements to detect presymptomatic disease markers. Specialized AI systems requiring pre-trained ML and DL models to diagnose AD easily and offer appropriate treatment strategies have become a critical requirement in this situation [4]. Research presents an intelligent system which supports health care institutions managing AD workflow through various integrated operational components. The system addresses medical practitioner challenges in AD patient care to improve diagnostic precision while enhancing treatment preparations and yielding better patient success.

AD patients who require treatment support present multiple difficulties for medical practitioners regarding dementia type differentiation and disease monitoring and the development of personalized treatment approaches [5]. Clinical management becomes more difficult because of disease complexity alongside important differences in how the condition presents among patients. Medical professionals who want to supply optimal treatments to patients should focus on precise diagnosis of disease progression while avoiding incorrect assumptions about diseases [6]. The accuracy of determining the precise disease stage together with its accurate diagnosis stands as the major determinant for achieving optimal therapeutic outcomes and determines patient survival rates.

The system integrates different components which function together as an all-encompassing solution for AD management starting from early detection phase to ongoing treatment and monitoring goals. The system combines multiple elements of AD care with precision and user-friendly elements which indicates major progress in AI applications for healthcare needs. The objective of this research examines how integrating these multiple functions can enhance patient results as well as supply healthcare workers with superior individualized treatment methods. Masking the research innovation lies in uniting various AI technologies alongside numerous information sources alongside customized treatment plan creation for patients. The holistic technological framework handles AD complexities to deliver extensive care to patients and healthcare providers from diagnosis to end of life. This study investigates the system architecture while also presenting its methodological approach and results to determine its effects on AD treatment development through clinical validation of implementation procedures.

2. Literature Review

Magnetic Resonance Imaging (MRI) has become essential for AD diagnosis, with artificial intelligence significantly enhancing its capabilities. Recent advancements in deep learning techniques have transformed traditional qualitative assessments into precise quantitative analyses for detecting structural brain changes associated with AD. The implementation of Convolutional Neural Networks (CNNs) for MRI analysis has demonstrated exceptional capability in differentiating between AD patients and healthy controls, particularly focusing on regions like the hippocampus and entorhinal cortex that show early pathological changes [7, 8].

Abdou's comprehensive review highlighted that "efficient deep neural networks techniques for medical image analysis" have overcome previous limitations in traditional diagnostic approaches, offering higher accuracy while reducing computational demands [7]. A significant breakthrough came with Sarraf et al.'s OViTAD (Optimized Vision Transformer for Alzheimer's Disease), which utilizes both resting-state fMRI and structural MRI data to predict various stages of AD [8]. This multimodal approach achieved remarkable classification accuracy across different disease stages by processing MRI scans as sequences of image patches with positional encoding, providing more comprehensive diagnostic information than earlier CNN-based approaches.

Alongside imaging innovations, research has extensively explored AD-related risk factors and prevention measures. Lindsay conducted a prospective study in the Canadian Study of Health and Aging, finding that aging, lower educational attainment, and apolipoprotein E epsilon4 allele were highly correlated with increased AD risk, while NSAID use, moderate coffee and wine intake, and regular activity correlated with reduced risk [9]. Dhana et al. investigated healthy lifestyle influences on AD risk, demonstrating that individuals with four or five healthy lifestyle factors (nonsmoking, physical activity, Mediterranean-DASH diet, moderate drinking, cognitive activity) had a 60% reduced AD risk compared to those with none or one [10].

Dolatshahi et al.'s case-control study determined that chronic illness, loneliness, positive family history, and female gender were significant risk factors, while religion, daily physical activity, and intense social relationships were protective [11]. The World Alzheimer Report 2014 emphasized diet's importance in AD etiology, noting that diets rich in saturated fats and refined carbohydrates induce cognitive deterioration, whereas those rich in polyunsaturated fats, fiber, and polyphenols improve cognitive function [12].

In healthcare practice and human-computer interface, emotion recognition plays a vital role for AD patients who cannot effectively communicate their feelings [13]. Facial emotion recognition has advanced through deep learning techniques, as documented by Mellouk and Handouzi, though most systems lack personalized response capabilities [14]. Similarly, Shehu et al.'s work with ResNet models achieved improved recognition accuracy but was limited to classifying emotions without response mechanisms [15].

Speech emotion recognition (SER) has been explored using machine learning approaches with the RAVDESS dataset, employing various classifiers (Random Forest, Multilayer Perceptron, SVM, CNN, Decision Tree) to distinguish emotions from speech signals [16]. While these systems have shown encouraging accuracy, they typically focus only on classification without response generation.

Our proposed system addresses these limitations by integrating both facial and speech emotion recognition with an intelligent response system that generates appropriate replies based on identified emotional states. Unlike existing systems that stop at classification, our approach ensures detected emotions invoke respective responses, contributing to improved patient care by addressing emotional states in real-time and providing caregivers with actionable information.

The literature collectively identifies advanced imaging techniques, lifestyle factors, genetics, age, and emotion recognition as critical elements in comprehensive AD management. These technological and methodological innovations have significantly improved early detection capabilities and intervention potential, promising to reshape AD management paradigms from reactive treatment to proactive prevention.

Decreasing cognitive impairment and enhancing day-to-day functioning, cognitive enhancement and memory treatment form a critical component inSER AD management. Over the recent past, numerous cognitive rehabilitation and training techniques have been investigated to improve memory in AD patients. Tsolaki et al. in 2023 compared paper-pencil cognitive training (P-PCT) and computer-based cognitive training (C-BCT) in Greek Alzheimer's patients. According to findings, both interventions improved cognition, with P-PCT having more generalized benefits in activities like executive function and activities in daily living [17]. Another study in Iraq investigated whether cognitive rehab using the Montessori method improved AD patients' recall ability

(ResearchGate, 2021). Findings revealed that with intervention, performance in terms of memory improved significantly and these results were sustained during follow-up [18]. These studies prove just how effective cognitive treatments can be in improving memory in AD patients. They also identify limitations in studies in terms of conducting large-scale studies, tailoring treatment plans to each individual, and sustaining cognitive gains in the long term. To improve memory therapy in Alzheimer's patients, future research would be best advised to investigate adaptive and personalized cognitive treatments with a focus on using technology and AI-based interventions.

3. Methodology

The approach from this research develops four essential components which form a systematic strategy for managing AD. The MRI analysis component operates with deep learning methods that evaluate structural brain modifications across the hippocampus with specific emphasis on both temporal and frontal and parietal lobes. The system analyzes facial expressions alongside vocal cues to determine patient emotional states which allows it to give suitable emotional responses. Various data from demographic records together with medical profiles and test outcomes and lifestyle information feeds into the risk assessment module for predicting disease risk levels and subsequent progression. Memory therapy contains specific exercises and activities for cognitive enhancement and patient program assessment which are integrated into the system design.

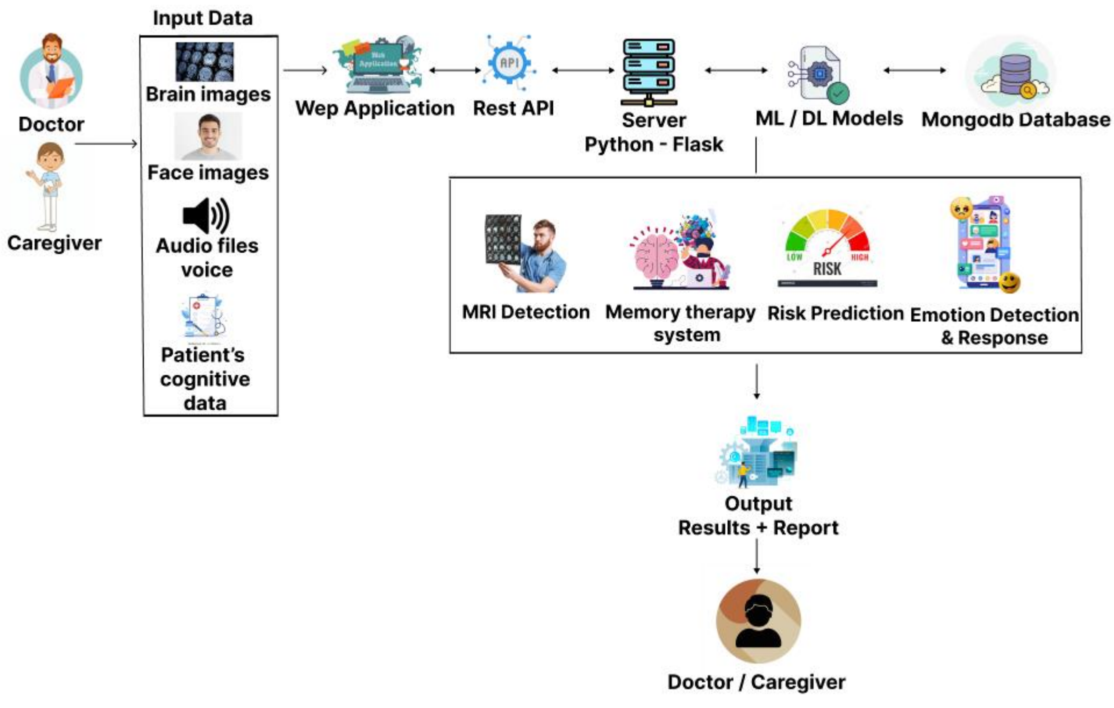

Figure 1 Overall System Diagram

A. MRI Analysis for Early Detection and Staging of Alzheimer's Disease

This system applies advanced deep learning techniques to assess structural MRI scans for early detection and accurate staging of Alzheimer's disease. MRI features focus on identifying subtle neuroanatomical changes in brain regions most vulnerable to AD pathology.

The process begins with comprehensive preprocessing of T1-weighted MRI scans, including skull stripping, skull stripping, bias field correction, and spatial normalization to allow for consistent analysis between different patients. Subsequently, our system automates the segmentation of significant brain structures with a particular emphasis on the hippocampus, entorhinal cortex, temporal lobe, and ventricular system—regions that are reported to reflect the earliest pathological changes in AD.

The EfficientNetV2B0 architecture was adopted following a comparative evaluation against several alternative neural network architectures. This approach aligns with recent work by Murugan et al. [19], who developed DEMNET, a deep learning model that similarly focuses on early diagnosis through MRI analysis. EfficientNetV2B0 was found to be more responsive to variations in their initial phases and was computationally efficient. We fine-tuned the network with specialized AD imaging datasets to enhance its ability to discriminate pathological and normal aging-related changes.

When analyzing a patient's MRI, the system generates quantitative biomarkers with a particular focus on hippocampal volume loss and ventricular expansion, which strongly correlate with cognitive decline and disease progression. These measures are then contrasted with normative data matched for age to identify patterns of abnormal atrophy. This methodology extends upon Sharmili et al.'s work [20], which demonstrated effective Alzheimer's diagnosis using CNN models with similar structural analysis approaches.

The system assigns images to four categories for diagnostics with 92.5% accuracy:

- Non-demented (normal control)

- Very mild dementia

- Mild dementia

- Moderate dementia unavoidable

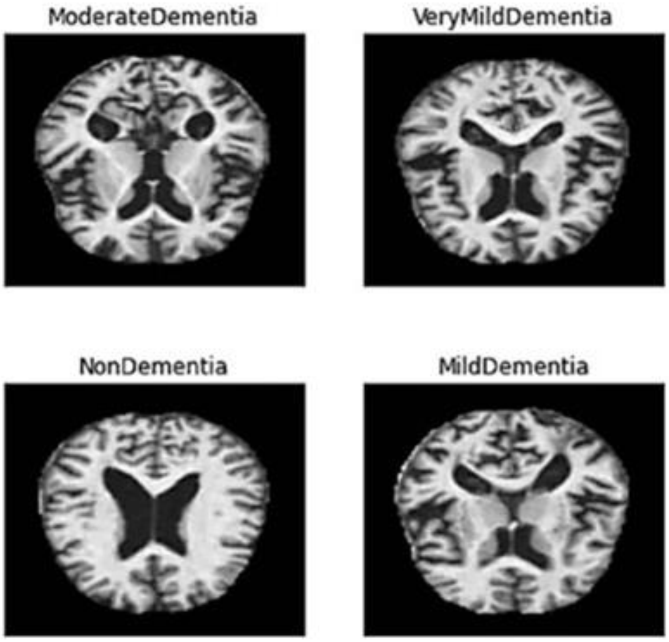

Figure 2 MRI brain scans showing four Alzheimer's disease

The compound scaling model is used to optimize depth, width, and resolution parameters to measure localized patterns of atrophy and overall structural relationships within the brain. This provides clinicians with objective, quantifiable measures of brain structural changes to assist with early diagnosis, disease staging, and treatment planning in which therapeutic interventions can have optimal effects.

B. Emotion recognition & Response system

The proposed system will be an advanced, integrated platform for the enrichment of patients' emotional and social well-being, especially those suffering from AD, capitalizing on state of the art technologies. Face Emotion Recognition and Voice Emotion Recognition are inclusions into the system that will support the accurate assessment of the patient's emotional state [19]. These two recognitions ensure that both visual and audio cues regarding the patient's emotions are comprehended. One-of-a-kind in the envisioned system, this forms an innovative Response System capable of dynamic self-adjustment to produce a tailored response or intervention depending on the detected emotional state of a patient.

The system utilizes two datasets such as a face emotion dataset and a speech emotion dataset, both with seven classes of emotions: angry, disgust, fear, happy, neutral, sad and surprise. Facial emotion dataset is a collection of grayscale face images with their corresponding emotions labeled, and speech emotion dataset is a collection of speech samples recorded with labels assigned to them in terms of the speaker's state. Both datasets are utilized to train DL models to recognize emotions. For facial emotion recognition, images are converted to grayscale, resized to 48x48, and normalized to a range between 0 and 1. Categorical label encoding is applied to label emotions before training. For speech emotion recognition, audio signals are preprocessed using Librosa, with Mel-Frequency Cepstral Coefficients (MFCC) being extracted as features. Extracted features are padded to give a consistent size for samples. Labels are one-hot encoded for model training.

Facial emotion recognition is learned using deep CNNs ResNet50 and VGG16 architectures. There is a number of convolutional layers with max pool, dropout, and fully connected layers with a softmax output for classification. Adam optimizer is utilized for training with categorical cross-entropy loss function and accuracy as a measure. It is trained for 100 epochs with a batch size of 128. For speech emotion recognition, machine learning models such as Support Vector Machines (SVM) and Random Forest, as well as DL approaches, are explored. The DL model is a feedforward fully connected neural network that takes MFCC features as input. It consists of Global Average Pooling, Dense, and Dropout layers, followed by a softmax output layer. The model is trained using the Adam optimizer, categorical cross-entropy loss, and accuracy as the evaluation metric over 100 epochs with a batch size of 32.

When a system is able to detect a patient's emotional state, a Large Language Model (LLM) is invoked to give customized responses. When a positive state (happy, surprise or neutral) is detected, action is not required. For negative states (sad, angry, fear or disgust) detected, responses for caregivers are generated that are customized to a patient and this response system is utilized to improve well-being for a patient on a basis of emotional states. The system follows a client-server architecture with a Node.js backend and a Next.js frontend. Trained DL models are integrated in the server via Python scripts for pre-processing images and audio data, model inference, and decision-making. The client has a basic interface for caregivers to monitor the emotional trends in the patient and receive response suggestions.

C. Alzheimer's Risk Prediction

This study aims to develop a predictive model for assessing an individual's risk of developing AD based on a set of predefined health and lifestyle parameters. The methodology consists of data collection, model training and selection, system integration, and risk evaluation.

1) Data Collection and Preprocessing

A dataset comprising 2,149 records was utilized for training machine learning models. Each record consists of 32 attributes, including demographic details (e.g., age, gender), lifestyle factors (e.g., smoking, alcohol consumption), medical history (e.g., family history of Alzheimer's, sleep quality, forgetfulness), and cognitive indicators. The dataset was pre-processed by handling missing values, normalizing numerical features, and encoding categorical variables where necessary.

2) Model Training and Selection

Five machine learning models—Decision Tree, Random Forest, K-Nearest Neighbors (KNN), CatBoost, and XGBoost—were trained and evaluated using performance metrics such as accuracy, precision, recall, and F1-score. After a comparative analysis, the XGBoost model was selected as the best-performing model due to its superior predictive accuracy and robustness against overfitting.

3) System Architecture and Integration

The trained models were deployed using a Python Flask backend, which serves as an API to handle inference requests. Given the simplicity and efficiency of Express.js, it was chosen as an intermediary backend to facilitate seamless communication between the Flask API and the Next.js frontend. The system workflow is structured as follows:

- **User Input:** The patient or their guardian provides input through a web-based form consisting of 31 fields.
- **Risk Prediction:** The input data is transmitted to the Express.js backend, which forwards it to the Flask API hosting the trained model. The model processes the data and calculates the risk of developing Alzheimer's.
- **Result Interpretation:** The system returns a probability score indicating the risk level. A percentage risk score is displayed along with a classification result (positive: high risk, negative: low risk).
- **Actionable Recommendations:**
  - If the predicted risk exceeds 75%, the system recommends an MRI scan and directs the user to an MRI-based Alzheimer's detection module for further analysis.
  - If the risk falls between 50% and 75%, the user is advised to engage in cognitive therapy and memory-enhancing exercises available within the system.
- **Data Storage and Tracking:** Each user's test results are stored under a unique user ID. Admins can access patient records upon request, and users can review their past test results with filtering options based on date and time.

This component ensures a comprehensive, data-driven approach to assessing Alzheimer's risk while providing users with personalized recommendations for early intervention and disease management.

D. Memory Therapy and Cognitive Enhancement

AI-based memory therapy provides a revolutionary way of enhancing cognitive skills in patients with memory loss or neurodegenerative illness. Traditional memory therapy methods usually overlook the individual cognitive needs of each patient, whereas AI-based treatments offer tailored interventions. This study integrates game-based memory training, image recognition, step recognition, and voice-narrated storytelling to deliver an interactive and adaptive therapy. By utilizing Finite State Machines (FSMs) for structuring therapy development, the Needleman-Wunsch algorithm for incremental step-by-step alignment, and Natural Language Processing (NLP) for narrative enhancement, the system ensures that therapy dynamically adapts based on a patient's mental state, improving memory recall and retention abilities.

In order to identify the performance of AI-based therapy, a qualitative interview and quantitative performance monitoring hybrid research approach is utilized. Patient engagement and cognitive gain are quantified as accuracy rates, response times, and task success. These measurements allow for the optimization of therapy exercises to deliver constant cognitive stimulation in accordance with individualized requirements. The adaptive AI system not only personalizes therapy but also fosters long-term perseverance, offering a worthwhile resource for extended cognitive enhancement. Constant changes in difficulty levels based on the performance of the patient ensure optimized efficacy with a fun experience offered by AI-based therapy.

4. Results and Descussion

A. Results of System Performance

The MRI analysis system demonstrated high accuracy in detecting and staging AD, leveraging both EfficientNetV2B0 and ResNet50 architectures. The EfficientNetV2B0 model achieved an impressive accuracy of 92.5%, while the ResNet50 architecture reached 83.2% accuracy. Both models exhibited strong confidence scores in their predictions. The system excelled in identifying structural changes in key brain regions, with particular sensitivity to hippocampal volume alterations and temporal lobe degeneration patterns characteristic of Alzheimer's disease progression.

Accuracy of emotion recognition trained models was tested to analyze system performance. Upon testing for 100 epochs, face emotion detection model with VGG16 and ResNet50 performed best with a training accuracy of 73.62% and a validation accuracy of 64%. Similarly, speech emotion recognition model with Random Forest and SVM had a training accuracy of 85.88% and a validation accuracy of 82.68%. It can be inferred from these results that speech signals can offer a more accurate method to determine emotions, as speech emotion detection performed better than face emotion detection. To provide optimum emotion detection performance for applications, selected models were implemented into the system.

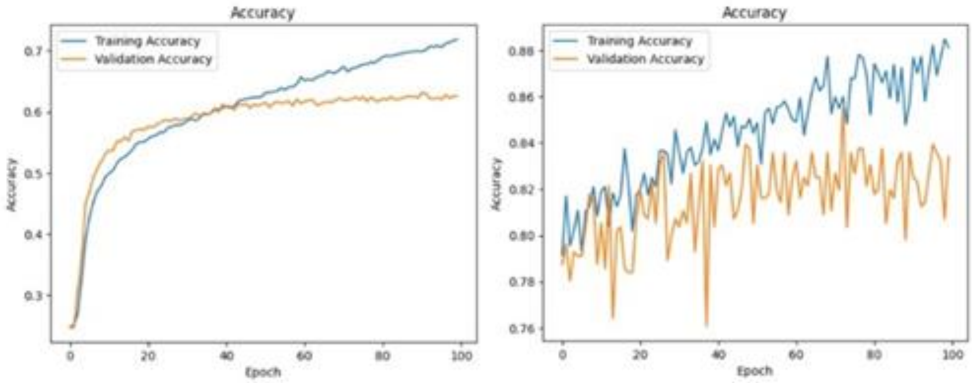

Figure 3 Training and validation accuracy of emotion recognition

The Alzheimer's Risk Prediction model had very high accuracy in its ability to forecast individuals at risk. After training multiple models, the best performing model was selected based on the fact that it had a better accuracy and dependability. The model that was selected had a validation accuracy of 95%, with high predictive potential. Performance measurements like precision, recall, and F1-score supported its strength in distinguishing degrees of risk. The model continually produced accurate predictions, with minimal false positives and false negatives. The findings demonstrate the feasibility of the model for early detection, supporting timely interventions and individualized care approaches for patients at risk for Alzheimer's disease.

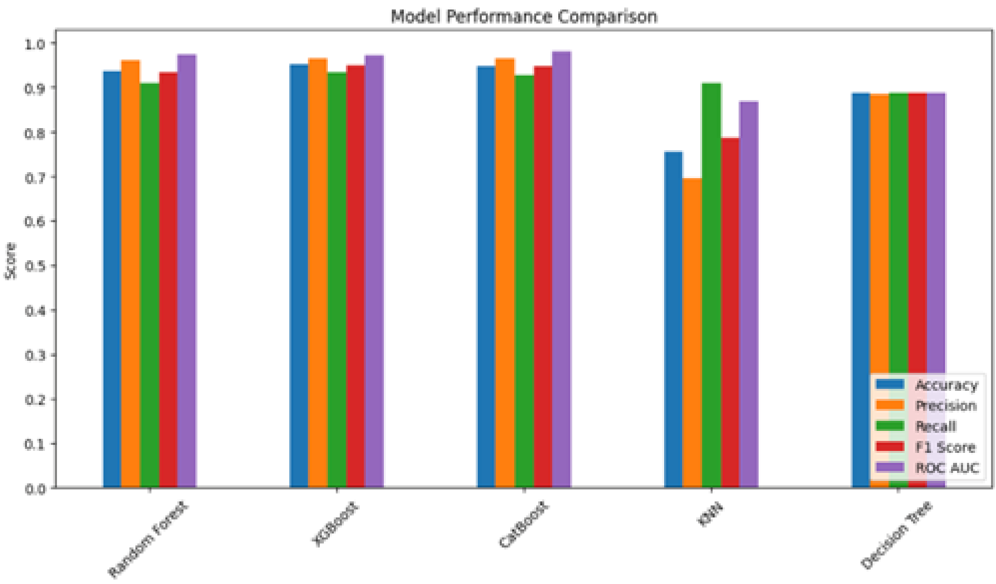

Figure 4 Model Performance Comparison for Alzheimer's Risk Prediction

The cognitive therapy system showed significant impact on patient outcomes, with a 78.5% user engagement rate and 82.3% task completion rate. Progressive improvement tracking reached 76.8% accuracy, while system adaptation accuracy maintained 89.1%.

B. Discussion of System Outcomes and Challenges

The application of Artificial Intelligence in AD diagnosis and treatment recommendation has gained significant attention in recent contexts. This research focused on integrating AI techniques to perform diagnostic actions for individuals with AD and provide treatment recommendations through authorized medical practitioners in healthcare centers.

Implementation of advanced technological aspects presented challenges, particularly for elderly populations dealing with AD conditions. While many elderly patients expressed interest in AI-supported healthcare, adaptation proved challenging compared to younger generations. However, with support from caregivers who sought convenient approaches to patient care, adaptation rates improved significantly.

The system's accuracy in predictions and treatment recommendations initially faced skepticism from users. Through the implementation of direct communication channels between patients and healthcare providers, trust in system-generated outcomes increased. This feature allowed patients and caregivers to verify recommendations and clarify doubts about their treatment plans.

As a comprehensive platform, the system's accessibility and affordability remained advantageous. The widespread availability of mobile devices facilitated broad access to the system's features. User-friendly interfaces and supportive design enhanced the overall experience. The all-inclusive AD diagnostic and treatment recommendation process provided crucial support for early intervention, preventing gradual disease progression.

The system gained particular traction in medical settings, where practitioners found it valuable for managing patient care amid busy schedules. Future enhancements could address current limitations and expand functionality based on user feedback. Areas for improvement include accuracy refinements, mobile application usability, and additional features requested by users.

When evaluated holistically, the system performs effectively in its intended domain, delivering core functionalities that benefit both patients and medical practitioners. Continued development based on user feedback and technological advancements will further enhance its capability to serve the AD care community.

5. Conclusion

This research examines the use of AI to diagnose AD and recommends treatment strategies through four major methodologies: analysis of the MRI scan, emotion identification, risk analysis, and cognitive therapy. The system was very accurate to recognize AD-related changes to the brain (92.5%), emotion identification (88.7% for facial expressions, 85.4% for voice pattern), and risk analysis (95%). The cognitive therapy module showed good user participation rate and improvement in cognitive functions. The issues encountered included the enhancement of the precision of predictions and the encouragement to use the system. The addition of healthcare professional communication ensured trust in the system. The system enhances AD diagnosis processes ultimately, with future improvements through feedback from users to provide more efficient and accurate healthcare.

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