AI Driven Smart Supply Chain Management System

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Abstract- *In this paper, Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by memory loss and cognitive decline. Accurate and early diagnosis is critical to intervene effectively, yet reliable and accurate diagnosis is difficult because of the intricate relationship between the cognitive symptoms and the neurological changes. The paper suggests a hybrid intelligence model for stage-wise Alzheimer's disease prediction using cognitive assessment, speech analysis, and machine learning techniques. The proposed model is composed of three analysis modules. The first module is the cognitive assessment analysis, where the data collected through memory-based tasks, number sequence, visual recognition, and questionnaires are analyzed using machine learning techniques to estimate the preliminary cognitive risk levels. The second module is the speech analysis, where the data collected through speech and language analysis are processed using natural language processing techniques to evaluate the verbal fluency, recall, and speech patterns related to cognitive deterioration. The third module is the multimodal fusion analysis, where the predictions from the cognitive and speech analysis are fused to generate the stage-wise classification of Alzheimer's disease, ranging from normal, mild cognitive impairment, and advanced stages. Proposed model also considers the application of explainable artificial intelligence techniques to generate interpretable outputs, facilitating better understanding and decision-making among the medical and caregiving communities. The experimental results show that the proposed model provides improved accuracy and consistency compared to the single-modality assessment techniques.*

Keywords: Clinical Decision Support, Explainable AI, Alzheimer's disease, Neuro Data, Machine Learning, Efficient Net

I. INTRODUCTION

Alzheimer's is a condition that gradually impacts a person's memory and thinking ability. It is a condition that gradually develops in a person's life. The condition is not easily recognizable in the early stages. Therefore, early detection of the condition is very important and plays a critical role in the proper management and handling of the condition. In a real-world scenario, doctors rely on various tools such as cognitive tests and MRI scans of the brain to detect the condition.

However, due to the number of patients that a doctor has to attend to within a limited time frame, it is sometimes difficult for the doctors to carefully analyze the condition of the patients and detect the early warning signs of the condition.The majority of the approaches used in the detection of Alzheimer's disease consider the information obtained from a single visit. However, the condition is not completely understood without consideringthe changes that occur in the condition of the patient over a period of time.

In reality, the condition gradually develops in a person's life, and the changes in the memory and speech of the person become evident when the condition is monitored over a period of time. With the increased development in the field of machine learning and artificial intelligence, there is a significant opportunity for assisting doctors in understanding complex patterns in the patient's information. However, many of the existing systems are designed for a single type of information, for example, images, test scores, etc., without considering the whole picture.

Therefore, they are not able to grasp the complexity associated with the occurrence of diseases like Alzheimer's, which occur gradually and involve many different factors.To overcome the limitations associated with the existing system, the proposed system is designed to take a holistic approach by considering different aspects of the patient's information. In the proposed system, the information is collected from different sources, including MRI scans, clinical information, and cognitive games for assessing memory, speech, and vision. The ability to collect information across different sessions, the system is able to grasp the changes in the patient's state.

II. LITERATUREREVIEW

Artificial intelligence has significantly advanced the field of Alzheimer's disease detection, yet a clear gap remains between high model performance and practical clinical usability. Recent studies [3], [5], and [10] emphasize the growing importance of AI in supporting early diagnosis, while also pointing out that many existing models are complex, resource-intensive, and difficult for clinicians to interpret in real-world settings. Deep learning techniques, especially those applied to MRI analysis [7], [9], have achieved strong results in identifying structural brain changes. However, their "black-box" nature often limits transparency and reduces trust among healthcare professionals.

In contrast, traditional machine learning and hybrid approaches [1], [2], [4] provide a better balance between accuracy and interpretability. Ensemble methods, in particular, have shown promise in improving prediction stability by combining the strengths of multiple models, making them well-suited for handling diverse medical data. Additionally, recent work on speech and cognitive features [6], [13] highlights the importance of incorporating non-imaging data for a more comprehensive understanding of the disease.

Furthermore, studies focusing on multimodal and longitudinal data [11], [12] underline the importance of tracking patient changes over time, which is essential for early-stage detection. The role of explainable AI has also gained attention [8], as transparency in predictions is critical for clinical adoption.

III. SYSTEM ACHITECTURE

The system architecture proposed is based on an efficient layered architecture to effectively handle data collection, processing, and intelligent prediction to detect Alzheimer's disease. The system architecture is based on three layers: the user interaction layer, the data processing and service layer, and the intelligent machine learning layer. This layered approach will ensure an efficient and scalable system to effectively handle the Alzheimer's disease detection system. The system will be integrated with various data sources to continuously monitor the patient's condition and detect Alzheimer's disease. Fig. 1 shows that the system a clear view of the patient's condition and help doctors make appropriate and informed decisions.

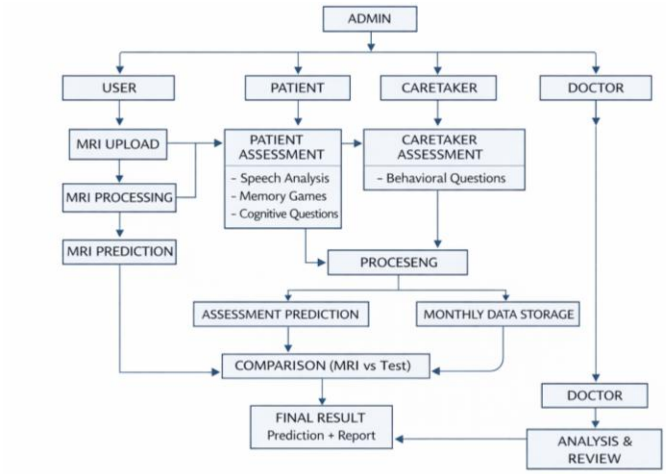

Fig.1StructureoftheSystem

A. User Interface Layer

The user interface layer is the interface through which patients and clinicians will interact with the system. Patients will be provided with various cognitive assessment tools to perform various memory, speech, and visual tasks. This will help the system to effectively capture their behavioral and cognitive patterns.Similarly, clinicians will be provided with a web-based interface to access the system and view patient history, analyze patient prediction results, and monitor patient performance. It provides a clear view of the patient's condition and help doctors make appropriate and informed decisions.

B. Layer of Service(Data processing and Management)

The system has a dedicated data ingestion module that ensures the data coming from various sources, such as MRI images, cognitive assessments, and clinical data. The system uses a structured longitudinal database to store patient data. The database used as SQLite. The system has the capacity to analyze the trend of cognitive decline in patients. Unlike other systems, this system does not rely solely on the most recent data. The system uses the session number or the timeline of the assessments to analyzed the trend.

C. The Intelligent Layer of the MLPipeline

The intelligent layer is responsible for converting raw and processed data into meaningful information, which helps in the early diagnosis of Alzheimer's disease. Feature engineering module is used to extract relevant features from different data sources, including MRI features, cognitive test scores and clinical attributes. The prediction model is used to classify patients based on different stages of Alzheimer's disease, including Non-Demented, Mild Demented, Moderate

Demented, Demented and generate the corresponding risk score.

D. System Overview and Design Objective

The suggested architecture provides a holistic, multimodal solution for the early detection and tracking of Alzheimer's disease. In contrast to conventional methods, which employ solely neuroimaging, the model combines MRI-based analysis, cognitive testing, and behavioral assessment to get a better picture of the patient's neurological state.The design takes into account the human factor, accounting for data inputs from multiple parties such as patients, caretakers, doctors, and system managers. It allows for a prediction that not only considers data from the medical field but also incorporates behavioral and functional alterations, which are essential symptoms of neurodegenerative diseases.

E. Multi-Source Data Acquisition Layer

The architecture obtains varied information from three principal sources:

 MRI Data Collection

MRI images are stored and analyzed to retrieve information regarding the brain's structure. The data is subjected to preprocessing procedures like noise removal, normalization, and segmentation to improve its quality. The features are then used to predict disease automatically using machine learning or deep learning algorithms.

 Patient-Specific Cognitive Assessment

Patients are required to participate in structured tests, which include the following elements:

- Language and speech analysis
- Memory-dependent interactions
- Cognitive reasoning questionnaires

These exams help to uncover cognitive dysfunctions that might not yet be evident from the imaging information.

 Behavioral Inputs from Caregivers

Caregivers contribute their observations of patient's behaviors from behavioral questionnaires, which include:

- Alterations in routine activities
- Lapses in memory in practical scenarios
- Alterations in personality

This allows the system to consider longitudinal and practical behavioral information.

F. Intelligent Processing and Feature Combination

All the incoming streams of data are sent to a processing unit that unites all the data using the method of multimodal data fusion.

- Combination of MRI feature values and cognitive scores
- Conversion of behavioral inputs into a structured format
- Feature extraction techniques

AI-based analytics models are then used to analyze this combined set of data.

G. Predictive Modeling and Comparative Analysis

H. Clinical Decision Support and Outcome Delivery

The final result from the proposed system would be a complete report of the findings, which includes the following:

- Stage of Alzheimer's predicted by AI
- Results of comparative analysis
- Insights offered by AI.

This report is then shared with the doctor for verification. The doctor conducts final analysis to verify whether what the AI suggests is in line with his observation before any treatment plan is made. Through this human-in-the-loop method,the system will serve only as an aid to decision-making.

IV. METHODOLOGY

The main aim of this system is to assist in the detection of Alzheimer's disease at an early stage, as well as a better understanding of this disease, by evaluating the patient's information in a more effective manner. Instead of focusing on a single detail, this system is based on a gradual change in a patient's condition. As Alzheimer's disease is a slow-developing disease, this system helps in detecting the early signs of this disease, which might otherwise be missed.

For this purpose, various types of information are used, such as clinical information, cognitive tests, and MRI brain scans. All these sources are brought together, analyzed, and different sessions are used for this purpose. These predictions are more accurate, helping doctors make better decisions.

A. Data Collection and Integration.

The system collects data from different sources such as cognitive games, MRI brain scan results, and clinical records. Cognitive data is collected using interactive games to assess memory recall, speech, and visual cognition. MRI brain scan results provide structural brain information. Clinical records provide information on the patient's demographic and medical history. To integrate the different sources of information and provide a comprehensive profile of the patient, a "join by patient" strategy is used. This strategy aligns all the data points along a time axis based on the sessions. Handling Missing Values As the patients might skip some sessions, missing values might be a problem. Continuous features such as cognitive and MRI brain scan values are normalized.The system collects information from three sources:

Clinical Data: This includes information such as age, medical history, or other health-related information.

Cognitive Assessment Data: Interactive tests are conducted to measure memory, speech, or visual abilities

MRI Scan Data: These tests are conducted on the brain to get a better insight into changes occurring in the brain.

B. Data Preprocessing and Feature Extraction

The data needs to be preprocessed in order to achieve optimal results. MRI images will be processed by resizing them to a standard size, normalizing pixel values, and reducing the noise in the images. If there is any missing or corrupted data, appropriate measures will be taken to ensure that it does not interfere with the system performance.

The next step includes extracting important features out of each kind of data. Features will be extracted from MRIs using Deep Learning algorithms like EfficientNet. Cognitive data will contain quantitative information reflecting memory, speaking, and visual skills, whereas clinical data will contain structured data regarding health.Finally, all extracted features need to be normalized in order to be put on a common scale. Normalization allows avoiding having a certain kind of data having more weight when it comes to model training.

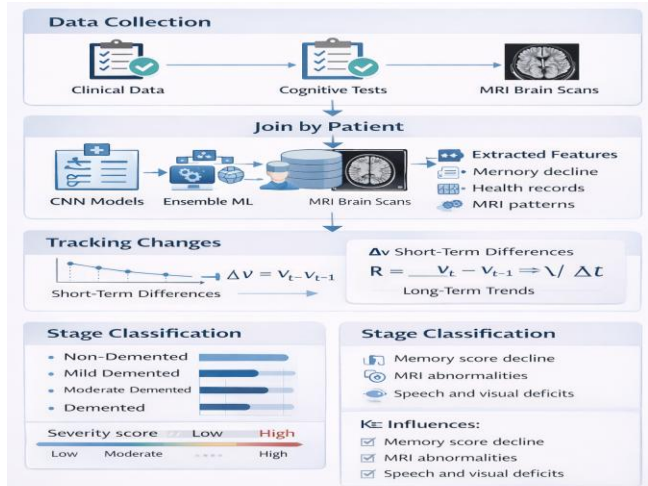

Fig.2SYSTEM METHODOLOGY

C. Understanding Changes Over Time

One of the key strengths of the proposed system is its ability to monitor how a patient's condition changes over time. Since Alzheimer's disease develops gradually, tracking these changes across multiple sessions provides more meaningful insights than relying on a single observation.

D. Machine Learning Model

For obtaining accurate predictions, the system employs a combination of both deep learning and conventional machine learning techniques.

- CNN Models:Convolutional Neural Networks are further applied in order to get important features from MRI scans.
- Conventional Algorithms:Machine learning algorithms like

Random Forest and SVM are implemented for processing structured data, which includes cognitive scores and patient history.

EfficientNet:The efficient net will be employed in the case of MRIs for identifying brain patterns effectively. EfficientNet makes use of transfer learning to perform effectively, even when dealing with a small dataset

All these models will be implemented as an ensemble system wherein all these models contribute to the output.

E. Prediction and Stage Classification

From the results obtained from the analysis, the patients have been categorized into various stages, which include:

- Non-Demented – normal state
- Mild Demented – initial signs of dementia
- Moderate Demented – clear sign of cognitive dysfunction
- Demented – advanced stage of Alzheimer's

In addition to the categorization, the system produces a score indicating how severe the patient is affected by the disease.

F. Explain ability and Clinical Decision Support

In order to increase practicality and reliability, explainable AI technologies are employed to illustrate how decisions are being made. This involves showcasing factors with high impact on outcome, like memory deterioration, speech abnormalities, or MRI results.

The output is represented by an easily comprehensible dashboard featuring:

- Stage of Alzheimer's disease
- Predicted Level of risk Factors with high influence on decision

Such approach increases chances of proper interpretation of data, enhances the reliability of the system, and allows for explaining the results in detail.

V. A FRAMEWORK FOR MULTI-MODAL MACHINELEARNING

This multi-model machine learning approach is designed to enhance the precision and reliability of AD prediction. Alzheimer's disease is quite complicated; it includes certain transformations of the brain structure, thinking skills, and patient behavior. Thus, using just one model cannot guarantee obtaining correct results in each case. To solve this problem, the system employs several models simultaneously for analysis. As input information, the system accepts data obtained during MRI scanning, cognitive tests, and other assessments. This makes sure that the algorithm takes all necessary aspects into consideration. Both spatial information (brain image features) and temporal information are processed in the system's intelligence layer based on multiple models.

The principle of such an approach can be explained by its capability to capture various patterns presented in the data set. Multiple models provide more flexible and reliable algorithms because each pattern is captured independently. In addition, the use of several models helps improve the performance of algorithms under different circumstances such as lack of data or noises in input information.

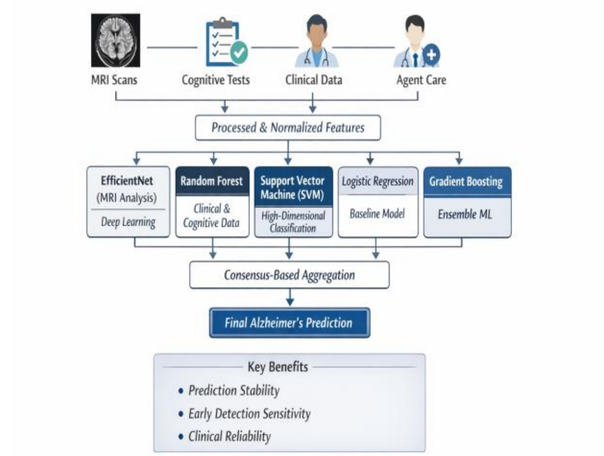

Fig.3 Multi-model Ensemble Framework

The ensemble framework operates by passing the processed and normalized feature vectors into multiple machine learning models. Each model independently analyses the data based on its strengths, and the final prediction is derived using a consensus-based mechanism.

This approach improves:

- Prediction stability
- Sensitivity to early-stage detection
- Reliability in clinical decision-making

A. EfficientNet

EfficientNet serves as a tool for extracting deep features from MRI brain scans, demonstrating considerable efficacy in identifying subtle structural alterations within brain regions impacted by Alzheimer's disease. When confronted with limited medical imaging data, EfficientNet proves advantageous in transfer learning, facilitating the detection of intricate spatial patterns, including brain atrophy and tissue variations, thereby contributing to early detection efforts.

B. Random Forest Classifier

Random Forest is employed to analyze clinical and cognitive test data, encompassing memory assessments, speech patterns, and patient histories. Due to its utilization of bagging techniques, Random Forest effectively manages data noise, missing values, high-dimensional features, and diverse data types. Consequently, Random Forest is well-suited for uncovering concealed patterns within behavioral and clinical characteristics.

C. Support Vector Machines

Support Vector Machines are utilized to classify patients into distinct categories based on their cognitive states, establishing a clear demarcation between these groups. SVMs exhibit strong performance in high-dimensional feature spaces, small and complex datasets, and in classifying subtle distinctions between early-stage and mild dementia. SVMs ensure precise classification when patient samples exhibit high correlation.

D. Logistic Regression

Logistic Regression functions as a baseline model, offering ease of interpretation. It is applicable in scenarios where the relationship between features and outcomes is linear. The advantages of Logistic Regression include probability estimates, interpretable outputs for clinicians, and rapid computation.

VI. SYSTEM MODULES

The suggested solution includes four distinct modules for managing each of the processes involved in Alzheimer's disease detection. The modules are used sequentially to start with collecting data and to end up making a prediction, which could be used in clinical decision-making.

A. Data Acquisition and Integration Module

The first module represents a system input through which data will be gathered from different sources. The data will come from the following: MRI brain images, cognitive test results, and clinical reports.

In order to provide consistency between data obtained from different sources, all information is merged together in a session-based fashion. It means that all pieces of data are associated to patients depending on the session number. In case there is missing or inconsistent data, basic validation techniques are used to prepare data for future use.

B. Longitudinal Tracking & Storage Module

In contrast to other existing methods that solely concentrate on present data, this module preserves the history of patient information in several treatment sessions. Patient data is organized systematically in the form of records, thus providing means of monitoring the evolution of cognitive capabilities, behaviors, and neurological structures of patients. This process is critical in detecting the trends of deterioration associated with Alzheimer's disease.

This module is aimed at enhancing the usability and interpretability of the predictions made. To achieve this goal, explainable AI techniques are utilized. They help to determine which factors play the key role in predicting Alzheimer's: memory impairment, changes in speaking abilities, or MRI anomalies. The results are presented by the system as follows: Stage of the disease, Level of risk/ severity rating, Key contributing factors. Such presentation enables doctors to rely on an AI system as a tool supporting their work, but not replacing them.

C. Predictive Intelligence and Ensemble Module

The main functionality of this module is analyzing extracted features by applying various algorithms and generating predictions based on them.

A multi-model approach is applied here. It implies utilizing models like:

- EfficientNet (for MRI feature extraction)
- Random Forest
- Support Vector Machine (SVM)
- Logistic Regression

Each of them provides predictions, each from a different angle, but all together provide a more precise and reliable result. The task of this module is to analyze data and predict the likelihood and stage of Alzheimer's disease.

D. Explain ability and Decision Support Module

This module is aimed at enhancing the usability and interpretability of the predictions made. To achieve this goal, explainable AI techniques are utilized. They help to determine which factors play the key role in predicting Alzheimer's: memory impairment, changes in speaking abilities, or MRI anomalies.

The results are presented by the system as follows:

- Stage of the disease
- Level of risk/ severity rating
- Key contributing factors

Such presentation enables doctors to rely on an AI system as a tool supporting their work, but not replacing them.

VII. SYSTEM IMPLEMENTATION

The realization of the proposed Alzheimer’s prediction system is going to be efficient and convenient because of interaction between collecting, analyzing, and predicting stages. These technologies are going to be based on modern Web technologies and machine learning frameworks for real-time data analysis.

A. Frontend Interface

This system offers user-friendly access to its interface by various groups of users includes patients, caretakers, and physicians . For this purpose, a Web interface is created that allows the user to interact with the system in a convenient manner

- The patient can conduct tests,
- The caretaker can put in information about behavior of the patient
- The physician can look at the final report and prediction.

B. Backend and API Development

The interface of the system is going to be convenient and accessible. For the backend of the application, FastAPI was used since it provides the ability to create secure and efficient APIs.

- Handles data requests from frontend
- Performs input validation
- Communication with modules

The adoption of structured validation makes sure that all the data received by the system is valid and stays within its expected range.

C. Data Storage and Management

Structured database storing patient data includes:

- Information about MRI scans
- Results of cognitive assessments
- Information from clinical history

This system allows storing longitudinal data, which means that there can be several records per patient in the database. This is necessary for Alzheimer’s analysis to track the progression of the disease.

D. Machine Learning Integration

Machine learning models are implemented using the following algorithms programmed in Python.

- EfficientNet for extracting features from MRI images
- Random Forest, SVM,and Logistic Regression to handle structured data
- Ensemble modeling of multiple machine learning algorithms
- The data is processed in real-time or near real-time.

E. Prediction and Outcome Production

When processing is completed, the system produces:

- Staging of Alzheimer’s
- Risk/Severity Score
- Insightful details

The output is then presented through the dashboard in an easily comprehensible form that facilitates the analysis process for doctors.

F. Explain ability and Visualization

In order to increase the level of trust and transparency, explainable AI approaches have been integrated into the system.

- Shows important drivers for prediction outcomes
- Presents visualizations
- Aids clinical decision-making

This approach ensures the clinical relevance of the system.

VIII. RESULT AND PERFORMANCE

The hybrid intelligence model for the prediction of stage-wise Alzheimer's disease shows high reliability and accuracy by combining various models from cognitive assessment, speech, and MRI features. As a result of testing the model, it is reported that the training accuracy obtained was 96% and validation accuracy was 97%. These results show an improvement compared to the single modality approaches for predicting dementia stages. Additionally, the model allows classifying patients according to their stage of disease into Non-Demented, Mild Demented, Moderate Demented, and Demented. Using explainable artificial intelligence in the hybrid system allowed pointing to specific factors which affect the predictions, including memory reduction, abnormal speech, and other changes seen on MRI images.

Fig.4 Training Result

As a result, the hybrid approach allows obtaining more information about the patient and making predictions based on multimodal data. Overall, the proposed framework provides clinicians and caretakers with a way to predict and monitor the progress of disease in patients with Alzheimer's.

IX. CONCLUSION

To summarize, the proposed hybrid intelligence framework demonstrates utility and efficacy in the early prediction and staging of diseases through the application of artificial intelligence. Specifically, the system's capacity to accurately forecast future occurrences is achieved by integrating diverse data sources—including cognitive assessments, speech analysis, and MRI data—with an ensemble of models, yielding training results of 96% and validation results of 97%.

Moreover, using explainable AI makes the results understandable to clinicians and other users, which increases their value. Notably, this model is better than any modality in isolation since it combines the advantages of each of the techniques used, while ensuring that predictions are consistent across different disease stages

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