Intelligent Dementia Prediction and Patient Monitoring Using Machine Learning and Deep Learning

[1]S.Sultana Farveen,[2]H.Rajeswary,[3]G.Pravin
*[*1]Senior Assistant Professor,[2]Assistant Professor,[3]UG Scholar*
Department of Electronics and Communiucation Engineering , RAAK College of Engineering and Technology,Puducherry,India

ABSTRACT :

Dementia is a progressive neurodegenerative disorder characterized by cognitive decline, memory impairment, and behavioral changes, which significantly affect an individual's independence and quality of life. Early identification of dementia risk factors plays a vital role in slowing disease progression and enabling timely medical intervention. This paper presents an intelligent mobile-based dementia prediction and remote patient monitoring system that integrates deep learning techniques with real-time caregiver support tools. A Recurrent Neural Network (RNN) model is employed to analyze sequential behavioral, cognitive and emotional data for the early detection of cognitive deterioration. The proposed system combines predictive analytics, live location tracking, mood monitoring, and personalized medication reminders within a unified mobile platform to ensure continuous patient supervision. Experimental evaluation demonstrates reliable performance in terms of accuracy, precision, recall and indicating the effectiveness of deep learning models in dementia risk assessment. The system aims to reduce caregiver burden, enhance patient safety and support proactive, data-driven healthcare decision-making through continuous monitoring and early warning mechanisms.

Keywords: *Dementia, Machine Learning, Deep Learning, Recurrent Neural Network, Cognitive Decline, Remote Monitoring, Mobile Healthcare.*

I.INTRODUCTION

Dementia is a progressive neurological disorder characterized by a decline in memory, reasoning ability, and daily functional skills, significantly affecting the quality of life of elderly individuals. Among its various forms, Alzheimer's disease accounts for the majority of cases worldwide. With the rapid growth of the aging population, dementia has emerged as a major public health challenge, increasing the burden on families, caregivers and healthcare systems. Early identification of cognitive decline is crucial, as timely intervention can help delay disease progression and improve patient management outcomes.

Recent advancements in Artificial Intelligence (AI), particularly in Machine Learning (ML) and Deep Learning (DL), have enabled the development of intelligent systems capable of analyzing large-scale medical and behavioral datasets. Deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have demonstrated strong potential in identifying hidden temporal and spatial patterns associated with cognitive deterioration. Unlike traditional systems that rely primarily on manual monitoring or isolated digital tools, AI-driven approaches provide predictive insights by continuously learning from patient data.

This paper proposes an intelligent mobile-based dementia prediction and remote patient monitoring system that integrates deep learning techniques with real-time caregiving support features. The system analyzes cognitive indicators, behavioral patterns, and emotional trends to estimate dementia risk and progression. In addition to prediction, the application offers safety-oriented functionalities such as live location tracking, personalized reminders, and emotional engagement tools to support both patients and caregivers. By combining predictive analytics with an integrated care platform, the proposed framework aims to enhance early detection, improve patient safety, and reduce caregiver burden through a scalable and secure mobile solution.

II.INTEGRATED ARCHITECTURE ILLUSTRATING THE COMPLEMETARY ROLES OF MACHINE LEARNING AND DEEP LEARNING

A. Role of Machine Learning

Machine Learning (ML) in the proposed framework functions as a structured data modeling and analytical component. Let the input feature vector be represented as:

$X=\{x1,x2,x3,...,xn\}$

where each x_i denotes clinical, demographic, behavioral, or sleep-related attributes. Supervised ML classifiers are trained to learn a mapping function:

$f_{ML}:X\rightarrow Yf$

where ,$Y\in\{0,1\}$ represents dementia risk classification (low/high risk).

ML algorithms estimate model parameters by minimizing a loss function $L(\theta)$, typically defined as:

$\theta*=\arg\min L(Y,\hat{Y})$

where,$\hat{Y}$ is the predicted output and θ denotes model parameters.

Within this project, ML serves three technical purposes:

- Baseline classification for structured datasets.
- Feature importance estimation to identify significant predictors.
- Performance benchmarking against deep learning models.

However, ML models treat each observation independently and do not explicitly model temporal dependencies. Therefore, their role remains supportive rather than central to longitudinal dementia progression modeling.

B. Role of Deep Learning

Deep Learning (DL) forms the primary predictive mechanism of the system. Since dementia progression is inherently sequential, the framework utilizes a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) units to model temporal dependencies.

Let the sequential input data be defined as:

$X=\{x1,x2,...,x_t\}$

where x_t represents patient features at time step ttt.

The hidden state update in an RNN is expressed as:

$ht=\phi(W_h h_t-1+W_x x_t+b)$

Where,
h_t = hidden state at time t
W_h, W_x = weight metrices
b = bias term

ϕ = non-linear activation function

To address vanishing gradient issues, LSTM units introduce gated mechanisms. The cell state C_t is updated using:

$C_t = f_t \odot C_{t-1} + i_t \odot \check{C}_t$
Where,
f_t = forget gate
I_t = input gate
$\check{C}_t$ = candidate state
$\odot$= element-wise multiplication
$\hat{Y} = \sigma(W_y h_t + b_y)$

where σ is the sigmoid activation producing a dementia risk probability.

Unlike ML, DL automatically learns hierarchical feature representations and captures long-term behavioral trends. This makes it highly suitable for early detection of cognitive decline from longitudinal data.

C.Integrated ML–DL Architecture

The proposed system integrates ML and DL into a unified predictive pipeline. Let the processed dataset be DDD. The ML module first evaluates structured risk patterns:

$Y_{ML} = f_{ML}(D)$
Where,
D =Input dataset

Simultaneously, the DL module processes sequential representations:

$Y_{DL} = f_{DL}(D_{seq})$

The final decision output is derived from the deep learning model while using ML results for validation and interpretability:

$Y_{final} = f(Y_{DL}, Y_{ML})$
Where,
D_{seq} = Denotes sequential data (e.g., time-series patterns like sleep, activity).
Y_{ML} = Output of the ML model
Y_{DL} = Output of the DL model
f_{ML} = Machine Learning model function that analyzes structured data.
f_{DL} = Deep Learning model function that captures temporal dependencies.

This hybrid framework enhances prediction robustness, improves generalization performance, and provides both interpretability (via ML) and temporal intelligence (via DL). The integration ensures reliable dementia risk estimation while maintaining computational scalability for real-time mobile deployment.

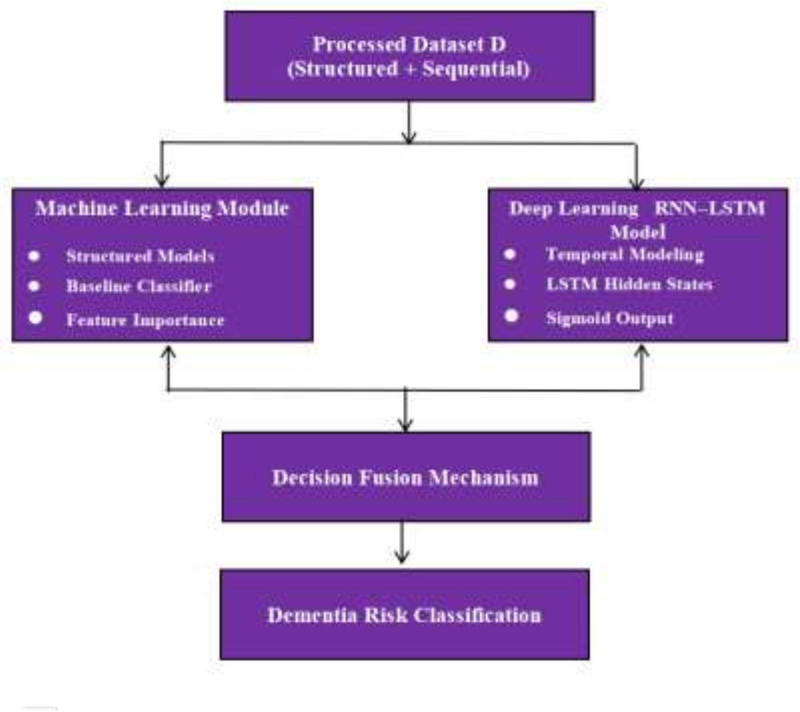

Fig.1 Integrated ML-DL Architecture

III.PROPOSED WORK

The proposed system integrates intelligent dementia prediction using neuroimaging data with a real-time remote patient monitoring framework. The system operates in three main phases: Training Phase, Testing Phase, and Monitoring Phase.

A. Training Phase

MRI brain images are collected from authorized medical repositories and labeled based on cognitive condition. The dataset is represented as:

$D=\{(X_i,Y_i)\},i=1,2,\ldots,N$

where X_i denotes the MRI image and Y_i indicates the diagnostic class.

Preprocessing operations such as noise removal, skull stripping, intensity normalization, resizing, and contrast enhancement are applied to improve image quality. Image normalization is expressed as:

$X_{norm}=X-\mu/\sigma$

Feature extraction is performed using convolutional layers to capture disease-specific structural patterns:

$F=f(W*X_{norm}+b)$

A CNN-based classifier is trained to predict dementia stages using the softmax function:

$P(y=j|x)=e^{zj}/\sum_{k=1}^{C} e^{zk}$

The training objective is to minimize the categorical cross-entropy loss:

$L = -\sum_{i=1}^{N} y_i \log(\hat{y})$

Model parameters are updated using gradient descent:

$W_{t+1} = W_t - \eta(\partial L/\partial W)$

B. Testing Phase

In the testing phase, unseen MRI scans are provided as input and processed using the same preprocessing and feature extraction steps as the training phase:

$F_{test} = f(W * X_{test} + b)$

The trained model predicts the cognitive state of the patient as:

$\hat{Y} = \arg\max P(y|X_{test})$

The predicted output is classified into Normal, Mild Cognitive Impairment, Moderate Dementia, or Severe Dementia. These results are stored and forwarded to the monitoring module for further actions.

C. Monitoring Phase

The monitoring phase enables continuous supervision of diagnosed patients. Patient information, medical history, emergency contacts, and medication details are securely stored in the database:

$DB = \{ID, History, Contacts, Medications\}$

Medication reminders are generated based on scheduled timings:

$$R(t) = \begin{cases} 1, & t = t_{scheduled} \\ 0, & Otherwise \end{cases}$$

Patient location is tracked using GPS, and the distance from the predefined safe zone is computed using the Haversine formula:

$$d = 2r \sin^{-1} \sqrt{sin^2(\Delta\emptyset/2) + cos\emptyset 1 cos\emptyset 2 sin^2(\Delta\lambda/2)}$$

An alert is triggered when the patient moves beyond the safe boundary:

$d > d_{threshold}$

Mood and behavioral patterns are analyzed using periodic inputs or sensor-based observations:

$M = 1/n \sum_{i=1}^{n} s_i$

All predictions, reminders, and monitoring records are stored in a centralized database with controlled access:

$Access = Auth(UserID, Password)$

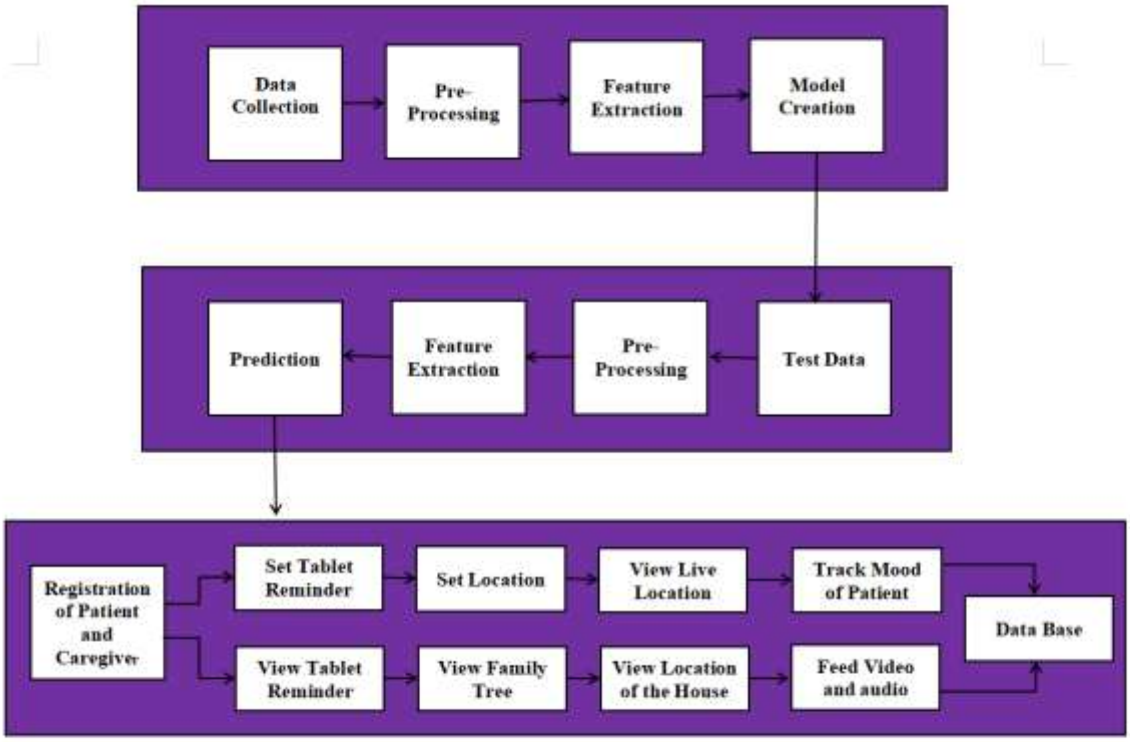

Fig.2 Architecture of the Proposed System

IV.SOFTWARE REQUIREMENTS

A. Operating System

The proposed Dementia Risk Classification and Monitoring System requires a stable and efficient operating environment for both development and deployment.

- For model development and backend implementation :**Windows 11 (64-bit)**
- For deployment : **Linux-based server (Ubuntu 22.04 LTS)**

B. Programming Language

- For implementing the machine learning and deep learning models : **Python 3.10**
- For mobile application development : **Dart**

C. Development Framework

For machine learning and deep learning model development:

- **TensorFlow 2.x**
- **Keras (integrated with TensorFlow)**
- **Scikit-learn**

Where,TensorFlow and Keras are used to implement the RNN-LSTM model for temporal data modeling, while Scikit-learn is used for structured data classification and baseline models.

For backend API development, the system uses:

- **Flask**

These frameworks enable communication between the mobile application and the trained machine learning models.

D. Libraries Required

The libraries are required for preprocessing, feature extraction, model training, evaluation, and visualization which includes:

For data preprocessing and numerical computation:

- **NumPy**
- **Pandas**
- **SciPy**

For deep learning (RNN-LSTM model):

- **TensorFlow**
- **Keras**

For visualization and analysis:

- **Matplotlib**
- **Seaborn**
- **Plotly**

For video and audio processing :

- **OpenCV**

These libraries collectively support structured and sequential data processing, model training, and performance evaluation.

E. Mobile Application Framework

The mobile application is developed using **Flutter**, a cross-platform framework that enables the development of Android and iOS applications using a single codebase.

The mobile application includes the following features:

- Patient and Caregiver Registration
- Tablet Reminder System
- Live Location Tracking
- Mood Monitoring
- Family Tree Visualization
- Video and Audio Feed Integration

F. Database

The system requires a database to store patient records, caregiver details, mood tracking data, location history, and model predictions.

For structured relational storage, **MySQL** or **PostgreSQL** can be used.

For flexible document-based storage, **MongoDB** may be utilized.

The trained machine learning model is stored in .h5 format and hosted either locally on the server or in cloud storage platforms

V.EXPERIMENTAL RESULTS

A. User Registration Interface

Fig.3 User Registration Screen for Patient and Caregiver

Fig.3 shows the user registration interface of the proposed healthcare app. Users enter basic details and select their role (patient or caregiver) to secure, role-based access. This module enables the personalized monitoring and data management.

B. Prediction Output

Fig.4 Dementia Risk Prediction using RNN Model

The fig.4 illustrates the dementia risk assessment interface of the proposed system. It highlights a **high dementia risk of 78%**, clearly indicating the severity level through a visual progress bar. The system demonstrates effective prediction accuracy by combining the user inputs with analytical models, supported by a trend graph that enhances reliability and the interpretability for decision-making.

C. Real-Time GPS Monitoring

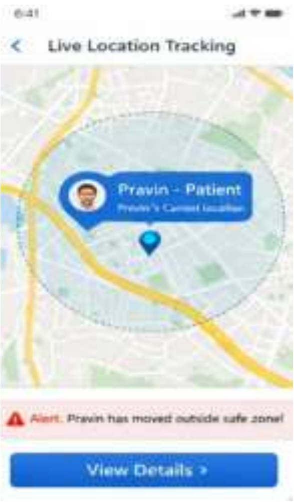

Fig.5 Live Location Tracking of Patient

Fig.5 represents the live location tracking module. It provides real-time map-based monitoring with defined safe zone and alerts when the patient moves beyond it, ensuring safety and timely caregiver intervention

D. Health Reminder System

Fig.6 Automated Water Reminder Notification

The fig.6 shows a hydration reminder interface in the mobile app. It provides timed alerts to drink water, with options to snooze or dismiss, along with a countdown for the next reminder. This feature supports daily wellness and habit formation.

E. Memory Support System

Fig.7 Family Tree for Memory Assistance

Fig.7 shows a family tree visualization module that hierarchically represents relationships among family members. It helps in understanding caregiving networks and supports efficient communication and monitoring within the system.

F. User Interaction and Notification Response Outcomes

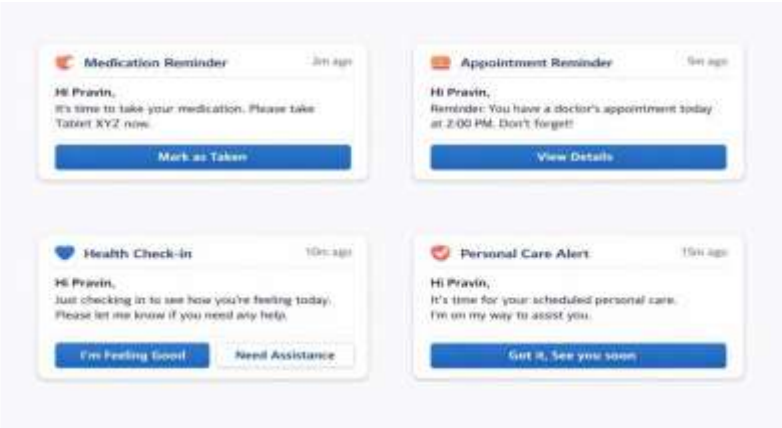

Fig.8 Medication and Appointment Reminder from Caregiver to Patients

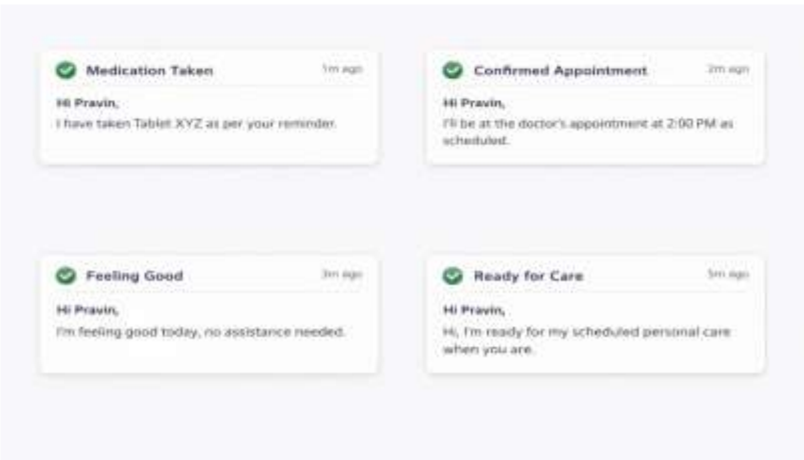

Fig.9 User Responses to Healthcare Notifications to Caregivers

Fig.8 and Fig.9 shows a notification-based healthcare support system with reminders for medication, appointments, and personal care. It enables user responses to alerts, improving engagement and adherence to daily healthcare tasks.

VI.CONCLUSION

The proposed work presents an intelligent and integrated framework for dementia prediction and remote patient monitoring by leveraging machine learning and deep learning techniques within a mobile-based platform. By effectively analyzing both structured and sequential data, the system enables early identification of cognitive decline, supporting timely medical intervention and improved healthcare outcomes. The use of an RNN-LSTM model enhances the ability to capture temporal behavioral patterns, resulting in more reliable and accurate predictions compared to traditional methods. In addition to prediction, the system incorporates real-time monitoring features such as live location tracking, medication reminders, and behavioral analysis, ensuring continuous supervision and improved patient safety. Experimental results indicate consistent performance across key evaluation metrics, demonstrating the system's effectiveness and practical applicability. Furthermore, the user-friendly interface facilitates easy interaction for both patients and caregivers, promoting better adherence to healthcare routines. Overall, the proposed solution provides a scalable, efficient, and user-centric approach to dementia care, contributing to improved quality of life for patients while reducing caregiver burden.

VII.FUTURE SCOPE

- Integration with wearable devices for real-time health monitoring (e.g., heart rate, activity tracking).
- Multilingual interface to support users from diverse linguistic backgrounds.
- Emergency alert system with features like fall detection and automatic caregiver notification.
- Integration with telemedicine platforms and electronic health records (EHR) for seamless data sharing.
- Enhanced data security through encryption and secure authentication mechanisms.

REFERENCE

1. Baker, S.; Warburton, E.A.; Thompson, R.; et al. *Early detection of cognitive decline using passive sensing and AI: A systematic review.* NPJ Digit. Med. **2022**, 5, 45.
2. Hampel, H.; Au, R.; Mattke, S.; et al. *Unraveling the complexity of Alzheimer's disease: The next step toward precision medicine.* Alzheimer's Dement. **2021**, 17, 1181–1202.
3. Jack, C.R., Jr.; Bennett, D.A.; Blennow, K.; et al. *NIA-AA research framework: Toward a biological definition of Alzheimer's disease—Update and perspectives.* Alzheimer's Dement. **2021**, 17, 123–143.
4. Rabinovici, G.D. *Controversy and progress in Alzheimer's disease—FDA approval of aducanumab.* N. Engl. J. Med. **2021**, 385, 771–774.
5. Milne, G.; McConnell, E.; Backhouse, T.; et al. *Digital technologies for early detection of dementia: A systematic review.* Ageing Res. Rev. **2021**, 67, 101327.
6. Gauthier, S.; Rosa-Neto, P.; Morais, J.A.; Webster, C. *World Alzheimer Report 2021: Journey through the diagnosis of dementia.* Alzheimer's Disease International **2021**.
7. Kourtis, L.C.; Regele, O.B.; Wright, J.M.; Jones, G.B. *Digital biomarkers for Alzheimer's disease: The mobile wearable devices opportunity.* NPJ Digit. Med. **2021**, 4, 9.
8. Petersen, R.C.; Lopez, O.; Armstrong, M.J.; et al. *Practice guideline update summary: Mild cognitive impairment.* Neurology **2020**, 95, 126–135.
9. Livingston, G.; Huntley, J.; Sommerlad, A.; et al. *Dementia prevention, intervention, and care: 2020 report of the Lancet Commission.* Lancet **2020**, 396, 413–446.
10. Ebenau, J.L.; Pelkmans, W.; Verberk, I.M.W.; et al. *Association of CSF, plasma, and imaging markers with cognitive decline in Alzheimer's disease.* JAMA Neurol. **2020**, 77, 1–10.