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An IoT-assisted Alzheimer's disease patient monitoring system using adaptive deep learning models with recommendation about patient abnormality

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Abstract

Internet of Things (IoT) has revolutionized healthcare by enabling continuous and real-time monitoring of patients, particularly for chronic diseases like Alzheimer's disease (AD). IoT-assisted monitoring systems leverage various technologies, such as sensors, wearable devices, and wireless communication, to monitor AD patients remotely. By integrating sensors such as electroencephalogram (EEG) monitors, Global Positioning System (GPS) trackers, and motion sensors, IoT systems can collect real-time data on the patient's behavior, health status, and location. This data is then transmitted to caregivers or medical professionals through cloud platforms, allowing them to monitor the patient's condition from a distance, assess cognitive functioning, and intervene when necessary. In this paper, an efficient AD patient monitoring system is introduced with deep learning. At first, the required EEG signals are gathered from benchmark resources, and then, wave and spectral features are extracted. The extracted features are then subjected to the Adaptive Dilated Gated Recurrent Unit (ADiGRU) for detecting Alzheimer patients. Here, the detection process is improved by optimizing the GRU's parameters using the Refined Alpha Value-based Dark Forest Algorithm (RAV-DFA). If the patient is detected with AD, then the patient is monitored by CCTV. Subsequently, from the surveillance monitored videos, the patient's abnormality is predicted by 3D Adaptive Residual Attention DenseNet (3DARADNet) and its parameters are tuned by RAV-DFA. If the abnormality is detected from the videos, then the recommendations are given to the concerned persons using Adaptive Generative Long Short-Term Memory (AGen-LSTM). For improving the performance of this phase also, the RAV-DFA is used, where the parameters of Gen-LSTM are fine-tuned. Thus, an effective AD patient monitoring system is implemented, and finally, the performance of this developed system is determined and contrasted with other related models for ensuring its supremacy.

Keywords: Alzheimer's disease patient monitoring system, Internet of things, Disease detection and abnormality prediction, Recommendation, Refined alpha value-based dark forest algorithm, Adaptive dilated gated recurrent unit, 3D Adaptive residual attention DenseNet, Adaptive generative long short-term memory

1 Introduction

AD is characterized by forgetfulness as one of its manifestations. However, it goes beyond this basic cognitive impairment. AD is a multi-disorder neurodegenerative disease that progresses over time [1]. According to the World Health Organization, 350 million individuals worldwide already suffer from Alzheimer's, and before 2030, that figure is expected to triple [2]. The main risk variable for the illness is age. It is possible to age without having AD, though. In a similar vein, the illness may start before age. Dementia is a sickness, not a result of aging naturally [3]. Patients with AD have imbalances when walking, decreased mobility, and muscular weakness. They have negative effects, including low blood sugar and disorientation, as a result of their drugs. Patients are at risk of frequent falls due to all of these variables [4]. Monitoring AD patients who live alone is unavoidable in order to offer prompt assistance in the event of such autumn episodes. Falls typically result in broken bones or head wounds. In the event of head trauma, these people might be in significant danger of hemorrhage and death if they are left untreated [5]. Fractures can also cause somebody to stay in pain for extended periods, which is a powerful incentive for the current study.

Treatment of AD takes into account the patient's complete medical history, psychological evaluation, mental observation, and physical analysis. Additional tests, like the mini-mental state examination, help evaluate mental health, including language, orientation, and decision-making abilities [6]. Classifying people as the key component of AD encourages a lot of research projects. Initial detection of dementia could help with early treatment and improve patients' general well-being. The discrepancy between the clinical information obtained and the facts inferred from it, nonetheless, does not appear to be conclusive [7]. The primary cause of this is the absence of a strategy for organizing and expressing relevant information that is specific to AD. No one algorithm might address the vast array of AD-specific domains on its own, and laborious effort is insufficient to acquire and decipher all pertinent disease-specific input [8]. This forces the creation of a lexical resource base tailored to AD, which serves as a bridge to remove semantic variety and makes it easier for wellness personnel and the diverse "things" in the IoT to transmit, share, and recycle data about healthcare. The merging of real and virtual items is made possible by IoT. Additionally, it encourages machine connection via the Internet, allowing information and facts to be shared to accomplish certain objectives [9]. This is accomplished by creating tailored intelligent services through the integration of devices, cameras, and processes. The proportion of fatalities in the USA that are ascribed to mental illnesses like Alzheimer's has increased exponentially, judging by data published by the National Centre for Health Statistics in 2017 [10]. The rise in these fatalities is ascribed to the fact that Alzheimer's disease is frequently discovered too late, making it extremely challenging to reverse the decline. Inadequate support systems for these individuals are cited as another factor [11]. These facts make it vital to have trustworthy technological resources for identifying and monitoring individuals with AD, such as observing them visually and then giving the support required for improved comfort of life [12].

Real-time data from smart healthcare facilities allow for ongoing tracking of patients. By linking computer networks, sensors, citizens, and goods, the IoT offers services with value [13]. IoT devices use Bluetooth, Wi-Fi, and an inexpensive Wi-Fi network to

connect. Innovative healthcare systems are created by combining the newest technology, such as cloud computing, artificial intelligence, IoT, and statistical processing [14]. In order to efficiently retain data and monitor the ailments of patients, smart medical facilities use wearable technology, the IoT, and apps. Medical professionals now find it easier to identify and cure clients because of smart systems of care and automated technologies [15]. The machine learning models reduce false positives in illness detection and produce highly accurate findings [16]. Real-time evaluation of patients is used for medical systems. Individuals with long-term health conditions who require immediate aid greatly benefit from these intelligent systems of care. Sensor-based smartwatches that send useful medical information to medical facilities allow constant device tracking [17]. As an alternative to the aforementioned need, several ideas have been attempted to develop various methods about AD diagnosis or forecasting. Several methods, including the use of motion sensing and MRI facts, are being used to forecast AD. However, the multifaceted solution for Alzheimer's recognition, tracking, and aid has not been fully accomplished by the current suggestions. Therefore, this work introduces an efficient AD patient monitoring system using IoT and deep learning methods.

Contributions The significant contributions of designed AD monitoring scheme are provided as follows:

- To utilize deep learning algorithms to monitor Alzheimer's patients continuously through EEG signals and video surveillance. By processing EEG data in real time, the system can detect early signs of AD and notify caregivers. Additionally, the system offers actionable recommendations based on the detected abnormalities, such as when a patient is at risk of wandering or falls. This real-time detection and recommendation mechanism allows caregivers to take timely actions, improving patient safety, and reducing the mental and physical burden on caregivers. The system ensures continuous monitoring, even when caregivers are not physically present.
- To propose the RAV-DFA, leveraging the Dark Forest Algorithm (DFA) is an advanced optimization technique applied to deep learning models in the system to improve their accuracy and effectiveness. This algorithm refines the parameters of deep learning models, helping them learn better from the data. In the context of this system, it enhances models like ADiGRU, 3DARADNet, and AGen-LSTM by optimizing hidden neurons in DiGRU, learning rate in DiGRU, ARADNet, and GLSTM, steps per epoch in DiGRU and ARADNet, activation function in ARADNet and GLSTM, and batch size in GLSTM. As a result, RAV-DFA increases the precision of AD detection, minimizes errors, and improves the overall system's performance in identifying abnormalities in patient behavior or neurological signals.
- To propose the ADiGRU model by the enhancement of the standard Gated Recurrent Unit (GRU) to process the sequential data. The addition of dilation makes ADiGRU unique, which is capable to capture long-range dependencies in different classes. For AD patients, subtle changes in brain activity can be spread across long periods, so detecting these patterns is crucial for early diagnosis. The ADiGRU can process this temporal data more effectively by zooming out and understanding longer sequences, which leads to more accurate identification of cognitive decline or neurological irregularities that indicate the presence of AD.

- To process video surveillance footage of AD patients to detect abnormal behaviors like wandering, falls, or disorientation, 3DARADNet is developed. 3DARADNet uses a 3D convolutional network, meaning it processes both spatial and temporal data to capture dynamic changes over time. The attention mechanism within this model ensures that the system focuses on important regions in the video frames, ignoring irrelevant information. This is critical because, in video surveillance, not all moments are significant to the health or behavior of the patient. By concentrating on abnormal movements or behaviors, 3DARADNet can effectively identify when a patient is at risk of harm (e.g., falling or wandering), providing caregivers with real-time alerts and improving overall patient safety.
- To suggest the AGen-LSTM, an extension of LSTM, it is efficient in handling sequential data. AGen-LSTM adapts to the evolving needs of Alzheimer's patients by generating personalized recommendations for caregivers. It takes input from real-time monitoring data and adjusts its outputs based on patterns in the patient's condition. For example, if a patient exhibits signs of increased confusion or disorientation, AGen-LSTM can suggest interventions such as adjusting the patient's environment, providing reminders, or even scheduling a medical consultation. The adaptive nature of AGen-LSTM ensures that the recommendations are not static but evolve with the patient's changing needs, improving the accuracy and relevance of caregiver advice.

Organization Overall work flow of developed model is given as follows: Sect. 2 includes literature survey; Sect. 3 offers designed AD patient monitoring system using EEG signal by extracting wave and spectral features; Sect. 4 provides the refined alpha value-based algorithm for optimizing the parameters with the introduction of AD detection using the dilated-based adaptive model; Sect. 5 shows the CCTV video surveillance for abnormal activity prediction and recommendation for affected patients using the adaptive deep learning model; Sect. 6 provides the results and discussion; and Sect. 7 provides the conclusion with future works.

2 Literature survey

2.1 Related works

Kaur and Sharma [18] have presented a novel Alzheimer's forecasting algorithm that makes use of deep hierarchical systems and the IoT. By integrating IoT devices to handle medical information, a new intelligent Alzheimer's outpatient surveillance network was created. In the beginning, improved Deep Residual Network-LSTM (DRN-LSTM) was used to identify people with Alzheimer's from the study group. Here, the individual's data were used to carry out an identification procedure. The local hospital was notified of the anomalous patients so that they might receive the proper care and observation. The precision and pinpointing percentage of the suggested Alzheimer's patient tracking device achieved 98% and 97% throughout the examination of the results.

Kayalvizhi et al. [19] have developed the innovative IoT Cloud-enabled Seamless Monitoring for Alzheimer Diagnosis and Rehabilitation System (SMART). Subsequently, the semantic modeling approach has been utilized to capture the relevant information to enhance the AD detection. Then, a Bayesian network selection simulation was constructed using the patient data gathered from things like sensory aids and components

from physicians and AD-trained professionals. A sensitivity assessment was also performed to confirm the developed model's resilience. The evaluation findings obtained for the actualization of the concept show great promise.

Sharma et al. [20] have suggested a DeTrAs: Deep Learning-based Internet of Health Framework for the Assistance of Alzheimer's Patients. Three stages make up DeTrAs's operation: (1) An ensemble method for deviation observing for people with AD was created, consisting of a pair of components: (a) a convolutional neural network (CNN) for emotion recognition and (b) a time-stamped window; (2) a neural network-based dementia forecasting initiative was put forward, employing sensory shift information. When compared to the various machine learning techniques already in use, the assessment of DeTrAs showed an efficiency gain of 10–20%.

Khalil et al. [21] developed an IoT model intending to locate a person with Alzheimer's in real time to enhance the quality of life and make their career jobs easier. Both the Internet app and an Android/iOS phone application provided a patient's position. Additionally, this study made it possible to track the patient's movement and use the Kalman filter to predict the exact location at all times, particularly when he walks outdoors. To show the usefulness as well as efficiency of the suggested prototype, several experiments were put forward.

Khosravi et al. [22] have presented a novel distributed learning-based identification framework using a deep CNN algorithm. This algorithm handled clinical data pictures from various sources, guaranteeing very accurate illness classification. It had a major influence on the early detection and management of AD and associated illnesses, which advanced the medical field and enhanced the quality of life for patients. These statistics improved the work's readability and gave consumers a better grasp of the analysis's findings.

Lakhan et al. [23] have suggested the Convolutional Learning Attention-Bidirectional Time-Aware Long Short-Term Memory (CL-ATBiLSTM) model as a deep learning method for classifying various AD stages. To deal with the dynamic character of EEG signals, the data were also divided into smaller windows. These windows were then converted into spectrogram pictures, which graphically represent the movement of brain function across time and frequency, including a 96.52% accuracy rate on Figshare databases. The method showed great promise for real-world application, speeding up the detection of AD, improving care for patients, and aiding in the creation of focused therapies for this crippling illness.

Manhua et al. [24] have developed an IoT model powered by artificial intelligence to track the health of patients with AD. Several modules were incorporated in the suggested smart medicine platform to track and notify AD patients about their health status. In this work, a Python computer vision model was used to identify fall occurrences. A smart medical system for AD patient tracking was suggested by this study.

Machado et al. [25] introduced an ontology-based computational model to identify possibly damaging behaviors for people with AD by using medical information from various IoT apps. This work's primary scientific achievement was the definition of an algorithm that focused on AD and used context history analysis and perspective prediction. Compared with the existing state of currently available art, this model became the sole study that used context history analysis to make predictions. Twenty

pertinent lessons on scientific, medical, and procedural elements were also learnt as a result of the studies, and these were documented in this work.

Mansingh et al. [26] have demonstrated a deep machine learning approach with techniques for detecting seizures using the EEG signal source. The details of time and frequency have been extracted by applying the CNN and RNN with an LSTM network. Subsequently, for obtaining the spectrogram and scalogram images, the STFT and CWT models have been employed. Finally, the better results were attained to achieve the supremacy of the system. Massoud et al. [27] have studied the Parallel Adaptive Feature Weight Fusion based on EEG-Dynamic Characteristics using a Channels Neural Network (PAFWF-EEGCNet) for diagnosing the drowsiness condition. The CWT technique has been used for retrieving the spectral and temporal features. Finally, these acquired features were fed into the model of attention and the parallel adaptive process of feature fusion to identify the mental state. Hence, the numerical findings have declared that the proposed system has achieved better performance.

2.2 Problem statement

AD is defined as a progressive disease caused in the brain that affects the thinking, memory, and reasoning skills. It has no permanent cure, yet timely recognition is vital. There is a significant requirement for observing the AD patients living alone to offer immediate support in case of certain fall episodes. Therefore, the recent innovations are highly considered for monitoring patients with AD. In AD patient monitoring, the IoT integrated with deep learning approaches can be leveraged to continuously gather the data from the wearable sensors, enabling the real-time validation of the patient's behavior, offering valuable insights for the caregivers, and allowing the timely identification of concerns and variations via the automated validation of activity patterns and movements, highly enhancing the life quality of the patients. Some significant problems related to AD prediction model are listed as follows.

- There are multiple patient monitoring systems have been implemented in the previous years for AD. However, these models have not performed well in the large-scale datasets. At the same time, the existing model's generalization is also poor. Therefore, designing an effective and generalizable model for AD patient monitoring is significant.
- Some existing AD patient monitoring systems have not performed the proper feature extraction, which reduced the efficiency of the model. Conventional techniques struggle to collect the highly complex features. Therefore, performing an effective feature extraction process is necessary.
- Some of the AD patient monitoring systems leverages machine learning models for detecting abnormalities. Though these models outperformed the traditional manual analysis, these models still demand the expertise of experienced clinicians to make the decisions. Therefore, suggesting deep learning models for monitoring the patients is significant.
- Though some existing AD patient monitoring models leverage deep learning for detecting abnormalities, these models face computational complexities and training

instabilities. Therefore, designing lightweight deep learning models for AD patient monitoring is significant.

- Several deep learning models have not provided satisfactory results in AD patient monitoring because of their own weaknesses. Therefore, designing an adaptive deep learning model using an improved heuristic algorithm is significant for achieving highly satisfactory solutions.

To address these challenges, a novel patient monitoring system was suggested by fusing IoT and deep learning technologies. A summary of the advancements and limitations of conventional AD monitoring models is presented in Table 1.

3 Proposed AD patient monitoring system using EEG signal by extracting wave and spectral features

3.1 Implementation of the proposed AD patient monitoring system

The challenges in diagnosing and caring for individuals with AD are multifaceted and complex, often arising from the gradual and unpredictable nature of the disease. One of the main challenges is the difficulty in diagnosing Alzheimer's in its early stages, as symptoms such as mild memory loss or confusion. The lack of definitive biomarkers for Alzheimer's makes it even harder to confirm a diagnosis through traditional methods [28] like physical examinations or cognitive tests. Additionally, the progressive nature of the disease means that symptoms worsen over time, and patients may struggle with tasks such as communication, self-care, and mobility. This can place a heavy burden on caregivers, who may face emotional, physical, and financial stress as they manage the patient's deteriorating condition. Moreover, the healthcare system may not always be equipped to offer the personalized care that Alzheimer's patients require, leading to gaps in the management and support of these individuals. Thus, this work developed a novel model for monitoring AD patients using deep learning, and Fig. 1 offers its architectural view.

The development of a novel AD patient monitoring system integrates deep learning techniques to facilitate early detection and continuous surveillance. By combining the power of EEG signal analysis, video surveillance, deep learning models, and real-time recommendations, this system offers a comprehensive solution for monitoring Alzheimer's patients. With its integration of cutting-edge technologies, the system provides a robust framework for enhancing patient care and improving the quality of life with AD.

The system begins with the collection of EEG signals from publicly available datasets. These EEG signals are vital as they reflect the brain's electrical activity, which can reveal patterns indicative of AD. The collected EEG data are processed to extract both wave features and spectral features, which are essential for distinguishing between healthy individuals and those exhibiting signs of cognitive decline. Wave features include different frequency bands such as alpha, beta, theta, and delta waves, while spectral features provide insights into the power distribution of these waves over time. Once the features are extracted, they are fed into an ADiGRU model, a deep learning architecture designed to analyze sequential data, such as EEG signals. The ADiGRU is then optimized using the RAV-DFA, a technique that fine-tunes the hyperparameters of the DiGRU model to improve the precision and reduce the

Table 1 Advancements and complications of prior AD patient monitoring systems using IoT

Author [citation]	Techniques	Advancements	Complications
Kaur and Sharma [18]	DRN-LSTM	It supports mitigating the gradient issues and is also efficient in collecting the long-term dependencies It highly improves the training stability and performs feature extraction efficiently	It is a relatively complex network and is easy to overfit Its training time becomes high, and it is hard to implement in real-time applications
Kayalvizhi et al. [19]	Bayesian network	It is simple to interpret and properly manage incomplete data It can model the complicated relationships among the variables	It highly depends on the expert's knowledge and demands more computational costs It also requires more amount of data that are not always available
Mohapatra and Mohapatra [20]	CNN	It is robust to noise and has high generalization It shows high accuracy and performs the learning process automatically	It utilizes more data and also takes more time for training Its computational power is high, and it is hard to optimize
Khalil et al. [21]	Kalman filter	It can handle uncertainty efficiently and eliminate noise efficiently It is computationally efficient and has the adaptability to changing conditions	It requires careful tuning of model parameters and is sensitive to the initial state estimations It cannot perform well in real-time applications
Khosravi et al. [22]	CNN	It extracts the necessary features quickly and performs hierarchical learning It is robust to image variations and performs tasks efficiently	It has interpretability complexities, and its demand for computation is high It faces overfitting and computational burdens
Lakhan et al. [23]	CL-ATBiLSTM and DWT	It concentrates on the highly significant features and results in highly accurate solutions It is highly suitable for large-scale data sources	Its network complexity and the computational cost are high It requires more training data and time
Manhua et al. [24]	AdaBoost	It can handle binary classification issues and also noisy data It is simple to understand and provides a high level of accuracy	It faces overfitting issues if it is not properly tuned It has limited flexibility and demands more resources for computation
Machado et al. [25]	Ambient intelligence	It improves the efficiency and user experience It can observe and respond to environmental variations according to the user's requirements	It faces the complexity of handling contextual data across distinct environments It lacks transparency, and the implementation cost is high

false-negative rate (FNR), and it enhances the ability to detect subtle patterns in the EEG signals, improving both the accuracy and reliability of AD detection. If AD is detected in the patient, the system proceeds to monitor the patient using CCTV surveillance. The integration of real-time video surveillance allows for continuous observation of the patient's behavior, which is essential for identifying potential risks such as wandering, falls, or other abnormal behaviors that often accompany

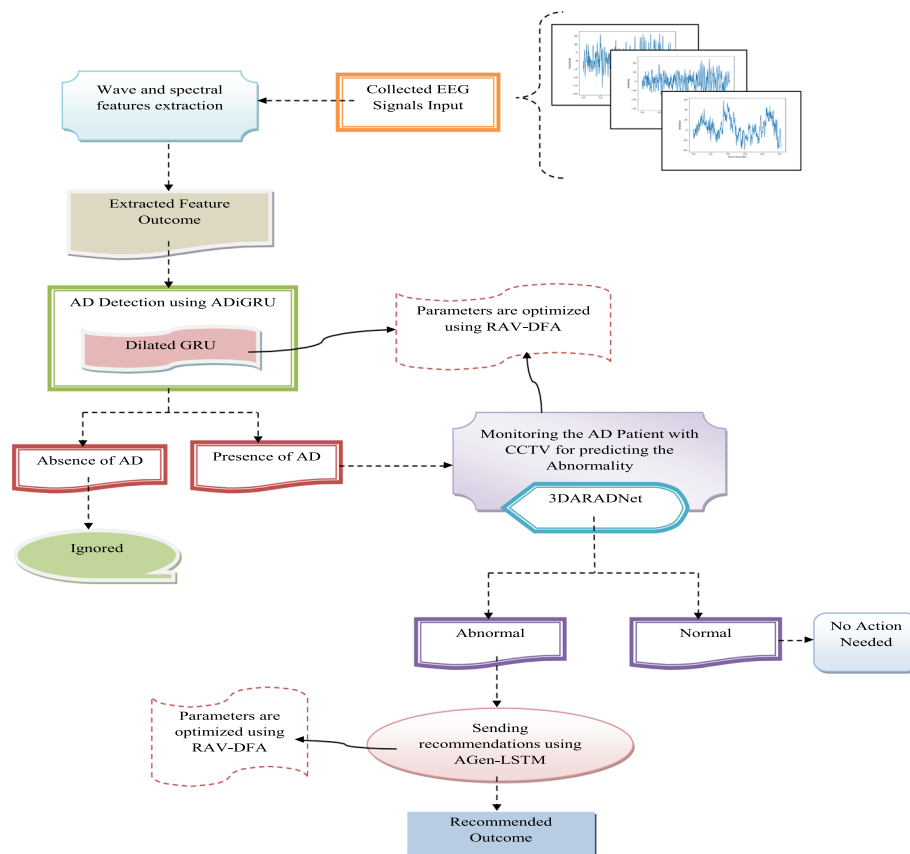


Fig. 1 Architectural view of the proposed AD patient monitoring system

the disease. The 3DARADNet is employed to analyze the video footage. This model is specifically designed for spatial–temporal data, making it particularly effective for video analysis. The 3DARADNet leverages attention mechanisms to focus on key frames in the video, such as moments when the patient exhibits signs of distress or abnormal activity. By using this model, the system can detect abnormal behaviors such as disorientation or mobility issues that are common in AD patients. As with the AD detection phase, the RAV-DFA is used to optimize the ARADNet network parameters, which improves the model’s ability to detect these abnormalities with high precision and intersection over union (IoU). The optimization ensures that the model is finely tuned to recognize even subtle changes in the patient’s behavior. Once an abnormality is detected, the system moves to the next phase of recommendation generation. Using the AGen-LSTM model, the system generates real-time recommendations for caregivers. These recommendations are based on the detected abnormal behaviors and aim to provide actionable insights to ensure patient safety and well-being. For example, if the patient is detected to be wandering, the system may recommend immediate caregiver intervention. The RAV-DFA is once again used in the AGen-LSTM phase to optimize the parameters of the model, such as activation function, learning rate, and batch size to improve the mean average precision (MAP) and hit rate, ensuring that the recommendations are timely, relevant, and accurate.

This iterative fine-tuning improves the overall performance of the system, making it more reliable and responsive to the evolving needs of the patient. Finally, the performance of this monitoring system is evaluated and compared against existing models to validate its effectiveness. The results from this comparison ensure that the proposed system outperforms related models, showcasing its potential as a superior tool for AD monitoring.

3.2 EEG signal collection

The developed AD patient monitoring system uses the required EEG signals from the standard resources, and its details are given as follows. Here, essential EEG signals are sourced from computational methods of EEG signals analysis for AD classification dataset and the EEG signals are collected from the link "<https://osf.io/2v5md/overview>: Access Date 2025-12-09." Moreover, the abnormality detection procedures are carried out in the developed AD detection model by considering the CCTV footage. Here, the samples used for abnormality detection are sourced from the benchmark dataset named Human Activity Recognition-Fall-Up dataset, and the required samples are collected from the link "<https://sites.google.com/up.edu.mx/har-up/>: Access Date 2025-12-09." Next, the collected video samples are processed using 3DARADNet to detect the abnormalities.

Purpose create a privacy-safe, reproducible dataset for training 3DARADNet with events relevant to AD patient monitoring.

Classes (5):

Normal Activity (walking, sitting, lying down).

Wandering/Aimless walking (prolonged roaming).

Fall—immediate (person collapses).

Fall—pre-impact (loss of balance + near-fall).

Prolonged immobility/Unresponsiveness (person on the floor/unmoving).

Samples & splits:

Total videos: 2,500 (balanced-ish): 500 per class.

Train/Test: 75% / 25% → 1,875 / 625.

Per-video duration: 6–12 s (variable).

Frame rate: 25–30 FPS.

Resolution: 640 × 360 or 1280 × 720 (prefer 720p for realistic CCTV).

Camera viewpoints: top/oblique/side; simulate fixed CCTV (mount) and hand-held (rare). Include at least 3 scene backgrounds (bedroom, living room, hallway).

Collected signal samples are specified by $\text{Sig}_H^{\text{EEG}}$, and samples are given in Fig. 2.

3.3 Wave and spectral features extraction

The collected EEG signals $\text{Sig}_H^{\text{EEG}}$ are forwarded to the feature extraction phase. Here, wave and spectral features were extracted. Wave and spectral feature extraction from EEG signals plays a critical role in the detection and monitoring of AD. EEG signals reflect the brain's electrical activity, and analyzing these signals can reveal important patterns that correlate with cognitive decline.

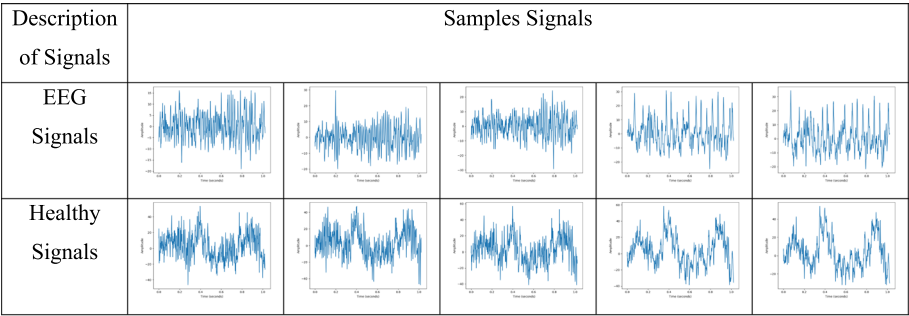


Fig. 2 Collected EEG signals from the dataset

3.3.1 Wave feature extraction

Wave feature extraction focuses on capturing the brain’s activity in different frequency bands, such as delta, theta, alpha, and beta waves, each associated with specific cognitive states. Delta waves are typically linked with deep sleep and lower levels of cognitive activity, while theta waves are more prevalent in states of relaxation or drowsiness, often increasing in Alzheimer’s patients. Alpha waves, which are associated with a calm, resting state, are also known to decrease in Alzheimer’s patients as cognitive functions decline. Beta waves are linked to active thought processes, and any abnormality in their pattern can indicate cognitive dysfunction.

3.3.2 Spectral feature extraction

Spectral feature extraction involves calculating metrics like power spectral density, which provides insights into the distribution of power across these frequency bands over time. Changes in spectral features, such as a decrease in alpha wave power or an increase in theta wave activity, can be indicative of Alzheimer’s progression. By extracting and analyzing these wave and spectral features, it becomes possible to detect subtle changes in brain activity, offering valuable information for early diagnosis and ongoing monitoring of AD. This process helps in understanding the underlying neural patterns associated with cognitive decline, enabling more accurate and timely intervention.

Finally, the extracted wave and spectral features are concatenated, and then, they are indicated by the term Ex_j^{Wa-Sp} .

4 Refined alpha value-based algorithm for optimizing the parameters with the introduction of ad detection using dilated-based adaptive model

4.1 Designed RAV-DFA-based parameter optimization

The RAV-DFA is an advanced optimization technique that enhances the performance of deep learning models in AD patient monitoring systems. Here, the RAV-DFA algorithm is designed based on the principles of DFA, which is inspired by the natural behavior of ecosystems. Also, the utilization of this algorithm helps in explore broader search space solutions to get the optimal outcomes.

Purpose of RAV-DFA A new optimization technique RAV-DFA is used to improve the AD detection process and abnormality detection in the video samples and to provide

better recommendations. In this research work, the developed RAV-DFA is employed to optimize the parameters of ADiGRU, such as steps per epoch, hidden neurons, and learning in specific ranges to enhance precision and reduce the FNR in the AD detection process. Then, different parameters like activation function, learning rate, and steps per epoch in 3DARADNet are optimized through RAV-DFA, which helps to enhance the precision of abnormality detection by reducing the IoU. Finally, at the recommendation phase, parameters of AGen-LSTM such as batch size, learning rate, and activation functions are tuned using RAV-DFA by improving the hit rate and MAP for recommendation efficiency enhancement in the complex classes.

Reason for choosing and modifying the DFA The major advantage of the DFA is its resistance to overfitting. Since the model uses multiple decision trees, the risk of overfitting is reduced because the trees are not likely to overfit the noise in the data. This makes DFA more robust in generalizing from training data to unseen data. This is valuable in fields like healthcare, where understanding the rationale behind predictions is crucial for trust and acceptance by domain experts and practitioners. Despite the advantages, it has certain limitations, primarily related to the alpha value, which controls the confidence and influence of individual trees in the decision-making process. These limitations can impact the overall performance of the algorithm, especially in certain applications. In many cases, the default or improperly set alpha value can lead to unnecessary complexity. The algorithm might generate overly complex decision trees that are difficult to interpret, especially if the trees are too rigid in their decision-making. The lack of fine-tuning on the alpha value means the algorithm may become unnecessarily complicated without providing a commensurate increase in predictive accuracy. To overcome these limitations, the RAV-DFA was developed, improving upon DFA by refining the alpha value to optimize model performance.

Novelty of RAV-DFA The RAV-DFA is an advanced version of the DFA that optimizes the alpha value using Eq. (1) to improve decision-making processes in deep learning models.

$$\alpha = \frac{Cft + (Bft)^2}{Cft + (Wft)^2} \quad (1)$$

Current fit is given as Cft, best fitness is presented as Bft, and worst fitness is represented as Wft. By refining the alpha value, RAV-DFA enhances the algorithm's ability to handle complex, high-dimensional, and noisy data. The refined alpha value improves the model's accuracy, adaptability, and ability to generalize, making RAV-DFA a powerful tool in the development of intelligent healthcare systems.

Advantages of parameter tuning by RAV-DFA This modification is particularly important in AD monitoring, where precision is critical. For instance, deep learning models like ADiGRU, which are used for classifying EEG signals, and 3DARADNet and AGen-LSTM, used for analyzing video surveillance data and recommendations, benefit greatly from this refined parameter optimization. The dynamic fine-tuning of RAV-DFA helps improve the performance of these models, leading to more accurate detection of Alzheimer's symptoms, abnormal behaviors, and cognitive decline, which is essential for timely intervention and support for caregivers. Additionally, the use of RAV-DFA significantly enhances the overall system's predictive capabilities. The dynamic alpha tuning enables

faster convergence during model training, reducing computational time, which is essential for real-time monitoring systems. This also ensures that the system can continuously adapt to new data, maintaining high accuracy and reliability over time, even as the conditions of the monitored environment change. As a result, the RAV-DFA-optimized Alzheimer's monitoring system can provide more timely, accurate, and actionable insights, improving patient care and reducing the burden on caregivers. Finally, RAV-DFA addresses the challenges posed by static optimization parameters in traditional DFA by refining the alpha value throughout the optimization process. This adaptability ensures a more efficient and accurate parameter tuning for deep learning models, improving the detection of AD symptoms, abnormal behaviors, and cognitive decline. The use of RAV-DFA enhances the overall performance of the Alzheimer's monitoring system, ensuring that it is more accurate, responsive, and adaptable to real-time patient data, ultimately contributing to better health outcomes and a reduction in caregiver stress.

DFA [29] DFA uses decision trees arranged in a forest structure to evaluate different potential solutions and optimize the decision-making process. The core of DFA is its ability to navigate through complex decision spaces to find the optimal model for classification or regression tasks. It initializes the population randomly using Eq. (2).

$$C_l^b = C_{l,\min}^b + \alpha \cdot (C_{l,\max}^b - C_{l,\min}^b) \quad (2)$$

here the b th element's initial factor is C_l^b , the candidate solution for the b th element's minimum score is $C_{l,\min}^b$, the maximum score is $C_{l,\max}^b$, and the term α is the random integer in the range of $[0, 1]$, and this gets updated by Eq. (1). Through this modification, RAV-DFA offers a more reliable and precise model for detecting abnormal patterns and predicting risks in AD patients, ultimately improving patient care and caregiver support. Figure 3 offers the flowchart of RAV-DFA.

4.2 Dilated GRU

By incorporating dilated convolutions, the DiGRU [30] is well suited to handle complex, high-dimensional time-series data, such as EEG signals in AD monitoring. It adapts unique features and ultimately makes more accurate predictions regarding the presence and progression of AD.

The GRU represents a streamlined modification of the LSTM architecture, designed to minimize computational complexity. This reduction is achieved by discarding the cell state and consolidating the traditionally separate input and forgets gates into a unified update gate. As a result, the GRU significantly decreases the number of parameters involved, leading to enhanced training speed and a more efficient convergence to optimal solutions. The architecture of the GRU is defined by two critical gates: the reset gate and the update gate. Initially, the reset gate is computed by evaluating the prior and present hidden state, with the process governed by a sigmoid activation function. This gate modulates the extent to which the existing hidden state is discarded, thereby controlling the degree of influence exerted by past information in updating the current hidden state. The behavior of this gate is articulated in Eq. (3), which specifies the mathematical formulation underlying this operation ρ .

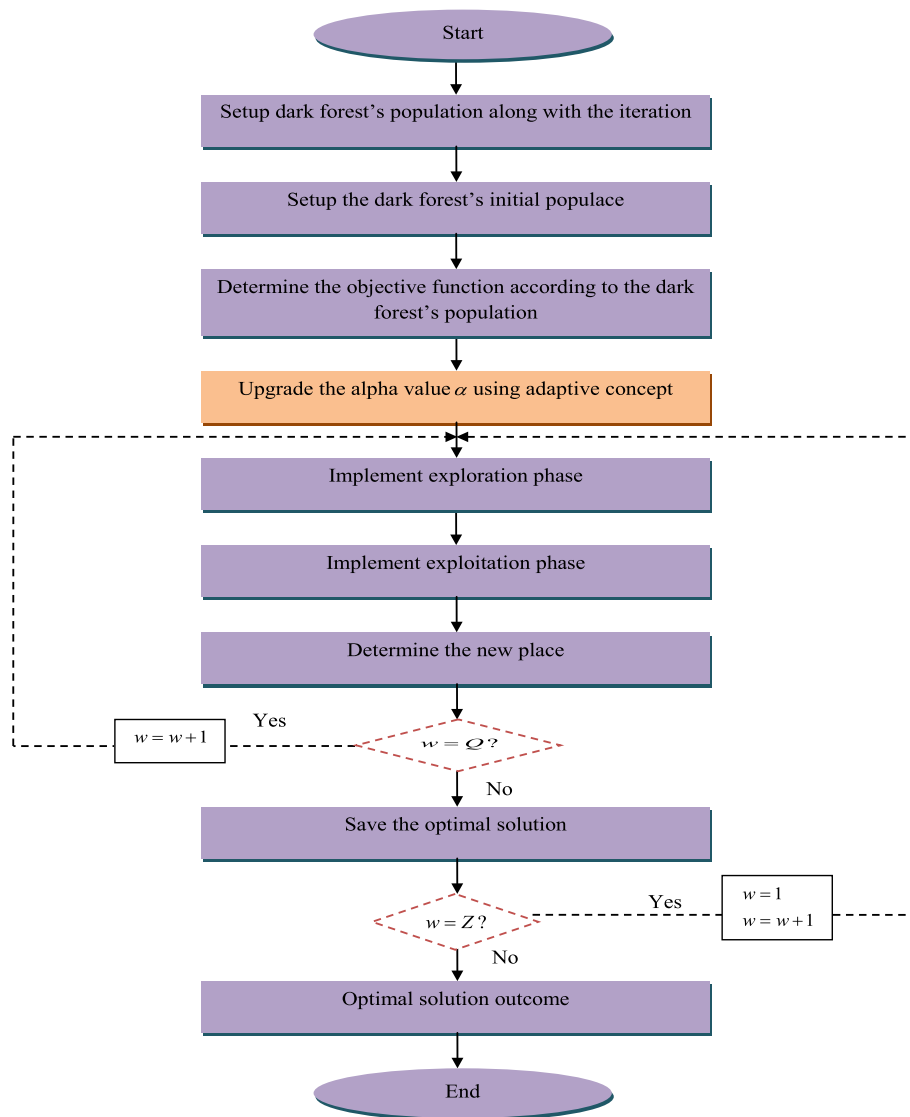


Fig. 3 Flowchart of the developed RAV-DFA

$$b_d = \rho(G_b \times h_d + E_b \times l_{d-1}) \quad (3)$$

In this representation, the weight parameters are specified as E_b and E_b , while present time step input is represented by h_d and the hidden state from the previous time step is denoted by l_{d-1} . The subsequent steps are as follows: (i) The reset gate performs a multiplication operation on the previous hidden state, which is then modified by an adaptable weight. (ii) A similar adaptable weight is applied to the input data at the current time step. (iii) The final result is obtained by summing the outputs from (i) and (ii), and the combined value is processed by the gating function $\tanh$. This entire procedure is captured by the expression in Eq. (4).

$$\bar{r}_d = \tanh(G_r \times h_d + E_r \times (b_d \times r_{d-1})) \quad (4)$$

The prospective latent state, or resultant output, is determined through the application of the function $\tanh$. When the value b_d approaches 1, it denotes a complete retention of all information from the preceding hidden state of r_{d-1} . On the other hand, when the value b_d tends toward 0, it implies the full exclusion or neglect of the prior hidden state's information. As delineated in Eq. (5), the final weight matrices associated with the update gate exhibit distinct variations in comparison with those of the reset gate, highlighting their differential roles in the model's information processing.

$$j_d = \rho(G_h \times h_d + E_j \times r_{d-1}) \quad (5)$$

The resulting outputs, which encompass the potential latent state, are amplified by a factor of two via the update gates, as expressed in Eq. (6).

$$r_d = (1 - j_d) \times r_{d-1} + j_d \times \bar{r}_d \quad (6)$$

After the preceding calculations, the latest and adjusted hidden state is retrieved. The adaptability of the model permits its utilization over various classes, thereby enhancing the accuracy of its results. Yet, it is constrained by the limitations inherent in its receptive fields, which restrict it to processing only shorter sequences of data for the execution of the task. So, dilation is added to it.

Dilated GRU The GRU model allows the convolutional intake of the sample sizes, also called dilated convolution, to address problems like limited receptive fields. Equation (7) may be used to compute the dilation $J(\cdot)$ procedure for a 1D time sequence input $H = (X_0, X_1, X_2, \dots, X_D)$ and screening $p : \{0, 1, 2, \dots, x-1\} \rightarrow B$.

$$P(D) = (H * {}_n p)(D) = \sum_{s=0}^{x-1} l(s).h_{D-n \cdot s} \quad (7)$$

here the dimension of the filtration is x , the movement of previous events is $D - n \cdot s$, and the dilation component is denoted by n .

4.3 Alzheimer's disease detection using ADiGRU

Purpose of ADiGRU The ADiGRU is an advanced variation of the standard DiGRU, which is designed to enhance performance in time-series data processing, especially for applications like AD monitoring. The developed ADiGRU is efficient in analyzing the sequential or temporal samples, like EEG signals. Here, the parameters of the developed ADiGRU such as learning rate, hidden neuron counts, and steps per epoch are tuned through RAV-DFA. Tuning the parameters supports to improve the overall precision and decrease the FNR for detecting the AD accurately among the individuals.

Design of ADiGRU The standard DGRU is specifically designed to handle sequences, using gates to control the flow of information and help mitigate the vanishing gradient problem. It has update gate and the reset gate, which control how much of the previous information should be retained and how much should be updated with the new data. This design is capable to collect the longer-range dependencies compared to traditional RNNs. Yet its computation expense is higher, and also, training the data samples takes more time. In some cases, they lead to the problem vanishing gradient and face some errors in collecting distant patterns. Hence, to tackle the above-mentioned issues, a dilated layer is used

with GRU, and the integration is named as DiGRU. Using the dilated layer in the GRU boosts the training efficiency and minimizes the parameter counts. Additionally, DiGRU is capable of collecting the sequential information from complex classes. Then, the parameters of DiGRU are tuned using RAV-DFA, and a novel implementation is termed as ADiGRU.

Novelty and working of ADiGRU In the AD detection phase, EEG signals are analyzed for specific wave and spectral features that indicate abnormal brain activity. Wave features include delta, theta, alpha, and beta waves, which are closely associated with different cognitive states. Spectral features, such as the power spectral density, further enhance the analysis by quantifying the distribution of power across these frequency bands, highlighting subtle shifts in brain activity that correlate with the disease's progression. The DiGRU model takes this extracted wave and spectral features Ex_j^{Wa-Sp} as inputs to detect AD. The input data, consisting of the time-series EEG signals and their associated features, are passed through the DiGRU model, which analyzes the temporal patterns to classify whether the patient's brain activity indicates the presence of AD. It is efficient to identify subtle changes in the time-domain EEG signals, such as irregularities in frequency band activity over time, enabling it to detect early-stage cognitive decline.

To further enhance the performance of the DiGRU, its parameters are optimized through RAV-DFA. RAV-DFA is an optimization technique that fine-tunes the model's hyperparameters, such as hidden neurons, learning rate, and steps per epoch to improve the precision and reduce the FNR. These parameters are crucial for ensuring generalization in unseen data and improve its detection accuracy. The RAV-DFA optimization process allows for a more precise fit to the training data, ensuring that network not only captures important features from the EEG signals but also prevents overfitting, which can occur when the model learns noise or irrelevant details in the training set. By refining these parameters, RAV-DFA helps to improve AD detection efficiency with higher accuracy and reliability. The outcome Di_p^{Detec} of this process indicates the presence of AD or not based on patient's EEG signals. This classification is essential for early detection, as identifying AD at an early stage allows for timely intervention and treatment, which can help slow the disease's progression. The DiGRU is optimized with RAV-DFA and therefore offers a powerful tool for accurately detecting Alzheimer's disease from EEG data, making it a significant advancement in early diagnosis and cognitive health monitoring. By incorporating the DiGRU model with RAV-DFA, healthcare professionals can rely on a robust system for identifying AD based on noninvasive EEG data, providing an effective and efficient alternative to traditional diagnostic methods. The model's ability to detect AD in its early stages based on brain wave patterns, combined with the optimization of its parameters using RAV-DFA, positions it as a valuable tool for clinical settings, where early diagnosis and intervention can significantly improve patient outcomes.

Objective function Objective function of developed AD detection model is signified in Eq. (8). The main aim of this ADiGRU is to maximize the precision and minimize the FNR.

$$OF_1 = \arg \min_{\{N_G^{DiGRU}, Lr_Q^{DiGRU}, Es_X^{DiGRU}\}} \left(\frac{FN_R}{Pr_{ec}} \right) \quad (8)$$

here the terms N_G^{DiGRU} , Lr_Q^{DiGRU} , and Es_X^{DiGRU} are the hidden neurons, learning rate, and steps per epoch in DiGRU in the bound $[5, 255]$, $[0.01, 0.99]$, and $[100, 500]$. The mathematical derivation for precision Pr_{ec} and FNR FN_R has been given in Eq. (9) and Eq. (10).

$$Pr_{ec} = \frac{Vq}{Vq + Mu} \quad (9)$$

$$FN_R = \frac{Ak}{Ak + pt} \quad (10)$$

here truly positive is Vq , falsely negative is Ak , truly negative is By , and falsely positive is Mu . Figure 4 provides the pictorial representation of designed ADiGRU-aided AD detection scheme.

5 CCTV video surveillance for abnormal activity prediction and recommendation for affected patients using the adaptive deep learning model

5.1 Residual attention DenseNet

The RADNet is designed by fusing the advancements of DenseNet, residual networks, and attention mechanisms to improve the performance of neural networks, particularly in tasks that involve complex, sequential, or large datasets. It efficiently captures both long-term

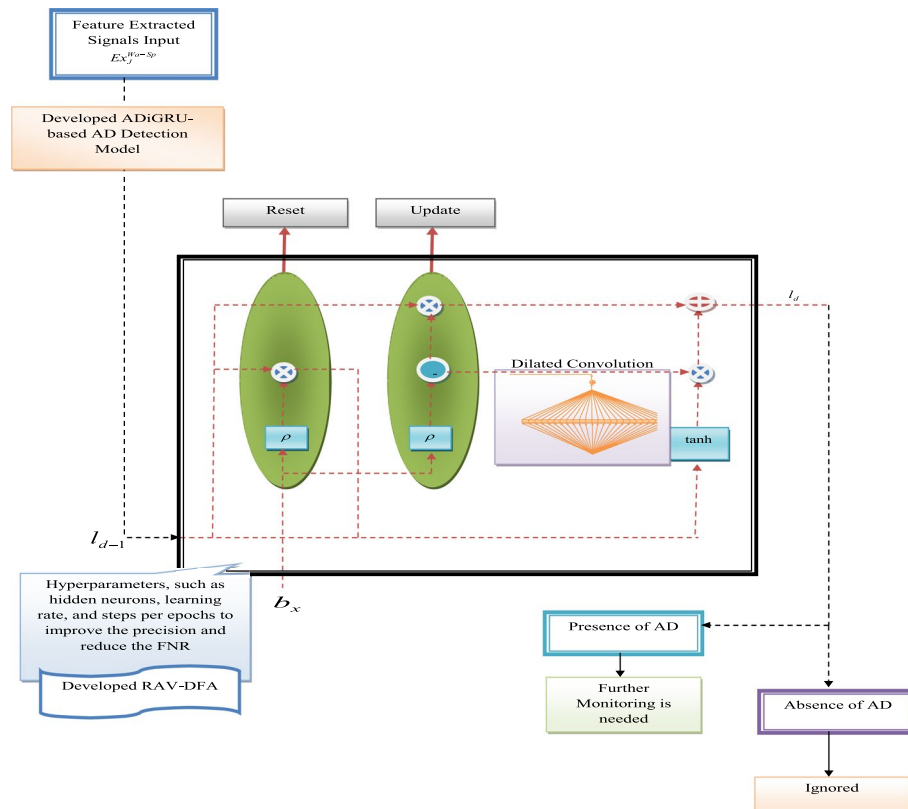


Fig. 4 Structural illustration of the developed ADiGRU-based AD detection model

dependencies and significant features in the data and also supports to obtain more precise prediction outcomes.

In residual DenseNet [31], each layer receives input from all previous layers, meaning each layer is densely connected to all the preceding layers. This improves feature reuse and helps in alleviating the vanishing gradient problem. Residual blocks in DenseNet make the network easier to optimize and enable the training of very deep architectures. The phrases J and K ones for the layout were used by residual DenseNet. This framework is thought to be the basic arrangement of the distinct elements that surface throughout the de-accumulation procedure. The web's information transmission capabilities are enhanced by the use of residual knowledge.

Dense approach The dense framework was the original network design used to establish multi-scale interactions. Convolutional layer's outcome is given in Eq. (11).

$$J_i = \diamond(A_i[J_1, J_2, \dots, J_{i-1}]) \quad (11)$$

The value $\diamond$ in Eq. (11) represents the rectified linear unit (ReLU), the weighted average about the i th convolutional layer is expressed by A_i , and the product of the translations that result from convolution and the creation of the $(i-1) \times K$ channel features map $(i-1)$ is expressed by $[J_1, J_2, \dots, J_{i-1}]$. Substantial dense characteristics with different sizes may be extracted according to the findings, which are derived from a variety of reactive area segments.

The i th convolutional layer creates a more condensed attributes map in this stage. For multichannel compression in the combined stages, the whole representational is divided into a few dense obstructions, each of which is passed via a 1×1 convolution. The dense components' J^j ultimate outcomes are explained by Eq. (12).

$$J_p^j = \diamond\left(A_i^j\left[J^{j-1}, J_1^j, J_2^j, \dots, J_{i-1}^j\right]\right) \quad (12)$$

Convolution p th in j th dense patch is denoted as J_p^j . Equation (13) displays the map's outcome considering $(j+1)$ th dense package, provided that it is the mathematical model of this process.

$$J^{(j+1)} = B^{(j+1)}\left(B^j\left(\dots\left(B^0(J_0)\right)\dots\right)\right) \quad (13)$$

The distinctive map between the inputs is given as J_0 .

To ascertain the correlation between several attributes, as well as the importance of the attributes and their impact on prediction, an attention method [17] is implemented. By using the attention approach to measure attention levels and capacity, the total amount for descriptions is determined. In addition to reducing computing costs, the attention-interconnected system also reduces resonance frequency and redundant trait correlations. Attention ratings of the attributes linked to the terms d_o and d_p are defined by the phrase g_{op} . Binary industries are located in Eq. (14), keeping the term g_{op} unconnected.

$$g_{op} = n^X UX(c_g(z_o \ominus z_p)d_o d_p + h_g),$$

$$g_{op} = \frac{\text{pex}(g_{op})}{\sum_{(o,p) \in V_b} \text{pex}(g_{op})} \quad (14)$$

The encapsulation depth can be expressed by p , and the application area of the hidden layer's attention system is given by X . The effectiveness of the ReLU UX , which is frequently employed as an indication of installation, was recently experimentally shown.

5.2 CCTV video surveillance for patients abnormal activity prediction using 3DARADNet

Need for abnormal activities prediction When AD is detected using the ADiGRU model, the next step in the monitoring process involves real-time surveillance using CCTV systems. The primary reason for integrating CCTV monitoring after detecting AD is to ensure the ongoing safety and security of the patient, especially as Alzheimer's disease often leads to various behavioral issues such as wandering, falls, and confusion, which can pose significant risks to the patient. Once the ADiGRU model identifies that a patient is exhibiting cognitive patterns indicative of Alzheimer's Di_p^{Detec} , it triggers the need for continuous monitoring via CCTV. This integration of technology ensures that the patient's actions are constantly observed in real time, allowing caregivers to respond quickly if abnormal behaviors or potential risks are detected. For instance, a person with Alzheimer's might try to leave their home, which could result in wandering or falling and having CCTV monitoring in place enables caregivers to intervene promptly before any harm occurs.

CCTV surveillance for abnormal activity prediction in Alzheimer's disease patients is an essential component of an integrated monitoring system aimed at ensuring the safety and well-being of individuals living with this debilitating condition. AD is leading to memory loss, confusion, and disorientation. These cognitive impairments often result in behavioral disturbances, such as wandering, falls, and other abnormal activities that can be dangerous if not detected early. In the context of AD affected patients, real-time video surveillance can be used to monitor and predict these abnormal activities, providing caregivers with timely alerts and the ability to intervene promptly before any harm occurs.

Purpose of 3DARADNet The innovative approach of using 3DARADNet for abnormal activity prediction in video surveillance leverages the power of deep learning and computer vision techniques. Traditional video surveillance systems often rely on basic motion detection algorithms or simple monitoring systems, which is not efficient in capturing the nuanced behaviors of AD affected patients. However, 3DARADNet, a deep learning model designed specifically for spatiotemporal data, is highly effective in analyzing video sequences, where both spatial and temporal aspects are essential for accurate activity prediction. Alzheimer's patients often exhibit unpredictable movements, and detecting these behaviors in real time requires a sophisticated model capable of identifying subtle changes in behavior that may indicate potential risks.

Implementation of 3DARADNet In the developed abnormal activities prediction phase, AD-detected samples Di_p^{Detec} are used as the inputs. One of the strengths of 3DARADNet is its ability to process video data using 3D convolutional layers. Unlike traditional 2D CNNs, which process individual frames or images, 3D CNNs can analyze a sequence of video frames as a three-dimensional volume. This network is capable to learn the temporal relationships between successive frames, as well as the spatial features in each frame. By combining both temporal and spatial analysis, 3DARADNet can identify dynamic actions and transitions in video sequences, which

are critical for detecting abnormal behaviors such as falls, sudden movements, or wandering. For example, when an Alzheimer's patient begins to stand up abruptly or moves in a way that could indicate a fall, 3DARADNet can detect these changes in behavior by evaluating the sequence of movements over time. Moreover, 3DARADNet integrates an attention mechanism that significantly enhances network efficiency in complex classes. Attention mechanisms are used in deep learning models to focus in the significant input data, giving more weight to critical features while ignoring irrelevant information. In the context of video surveillance, this attention mechanism supports to prioritize specific moments in the video where abnormal activities are most likely to occur, such as a sudden movement or change in posture that could indicate distress. By focusing on these key moments, 3DARADNet improves the accuracy of abnormal activity detection and reduces the likelihood of false positives or missed detections.

Another significant aspect in 3DARADNet is parameter tuning using the RAV-DFA. RAV-DFA is an advanced optimization technique that fine-tunes the hyperparameters of the model, such as activation function, learning rate, and steps per epoch, improving the capability to detect these abnormalities with higher precision and intersection over union (IoU). Optimizing these parameters is crucial for improving the model's ability to generalize to new data, ensuring that it can make accurate predictions on a wide variety of video sequences. In real-time monitoring, the model must process video frames continuously and make predictions in near real time. Optimizing the network parameters through IDFA ensures that the 3DARADNet model can handle large volumes of data efficiently, without compromising on prediction accuracy or computational speed. The real-time video surveillance system using 3DARADNet not only improves the safety of Alzheimer's patients but also reduces the burden on caregivers. Constant monitoring and prediction of abnormal activities help prevent accidents, minimize the risk of falls, and ensure that patients are properly cared for. The advanced deep learning techniques employed by 3DARADNet enable a higher level of precision in detecting complex behaviors, offering an essential layer of protection for Alzheimer's patients. Finally, the patients abnormality-predicted outcome is indicated by the term Ab_V^{Pred} .

Advantages of 3DARADNet The real-time video surveillance for abnormal activity prediction using 3DARADNet offers a promising solution for improving the safety and quality of life of individuals with AD. By leveraging deep learning, 3D convolutional networks, attention mechanisms, and optimization techniques like IDFA, this system can accurately predict and detect abnormal activities in real time. These advancements in monitoring technology significantly enhance the caregiving process, providing caregivers with the tools they need to ensure patient safety and well-being. With the increasing prevalence of AD and the growing demand for effective care solutions, real-time video surveillance using 3DARADNet stands as a crucial step forward in the development of innovative monitoring systems for Alzheimer's patients.

Objective function Eq. (15) represents the objective function of designed 3DARADNet-based abnormal activity prediction mechanism. The main aim of this model is to maximize the precision and IoU.

$$OF_2 = \arg \min_{\{E_p^{RADNet}, Lr_Y^{RADNet}, Es_L^{RADNet}\}} \left(\frac{1}{Pr_{ec} + IoU} \right) \quad (15)$$

here the terms Af_p^{RADNet} , Lr_Y^{RADNet} , and Es_L^{RADNet} are the activation function, learning rate, and steps per epoch in RADNet in the range of [1, 5], [0.01, 0.99], and [100, 500]. The mathematical derivation for precision Pr_{ec} and IoU has been given in Eqs. (9) and Eq. (16).

$$IoU = \frac{|Cg \cap Wf|}{|Cg \cup Wf|} \quad (16)$$

here the term $|Cg \cap Wf|$ indicates the intersection and $|Cg \cup Wf|$ signifies the union among the bounding boxes of ground truth as well as detected.

The pictorial view of designed 3DARADNet-aided CCTV video surveillance scheme for abnormal activity prediction is provided in Fig. 5.

5.3 Generative LSTM

In the context of AD patient monitoring, Gen-LSTM [32] plays a crucial role in handling and generating meaningful insights from sequential data related to the patient's condition, such as EEG signals, behavioral patterns, CCTV surveillance videos, or

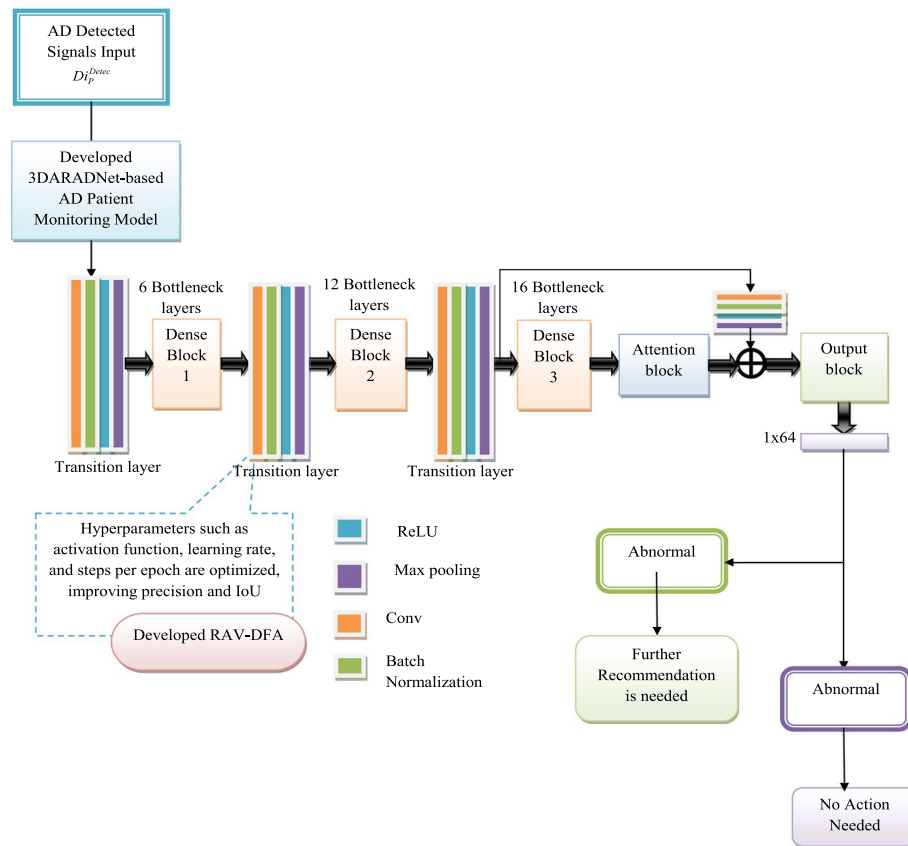


Fig. 5 Pictorial view of the developed 3DARADNet-based CCTV video surveillance model for abnormal activity prediction

health-related time-series data. The core strength of Gen-LSTM lies in its ability to model complex, temporal relationships within data, which is essential for monitoring the progression of Alzheimer's and offering timely interventions.

The learning outcome of the RNN influences the LSTM. For running the data about the cycle, the RNN receives backing. To understand the long-term interdependence between the components, the LSTM is provided. The long-term time series is calculated by utilizing the LSTM. Consequently, these gradient issues may be resolved using the LSTM. The output, input, and forgets gates are the three kinds of gates used in LSTM. These controls aid in the selection of data to retain. The LSTM uses short-term storage to keep gradients from vanishing by swapping out the gates. The current input vector $f_{(b)}$, the LSTM's prior cell state $y_{(b-1)}$, and the conventional secret states $m_{(b-1)}$ constitute its inputs from the outside.

The following describes the LSTM evaluation procedure in its entirety.

$$j_{(b)} = \mu(H_{jf}f_{(b)} + H_{im}m_{(b-1)} + q_j) \quad (17)$$

$$r_{(b)} = \mu(H_{rf}f_{(b)} + H_{rf}m_{(b-1)} + q_r) \quad (18)$$

$$s_{(b)} = \mu(H_{sf}f_{(b)} + H_{sm}m_{(b-1)} + q_s) \quad (19)$$

$$y_{(b)} = \tanh(H_{yf}f_{(b)} + H_{ym}m_{(b-1)} + q_y) \quad (20)$$

here the weighing factors are H_f and H_m and the biased parameter is q . The data point $\tanh$ is the sigmoid functioning, and μ represents the nonlinear trigger function.

Additionally, Eqs. (21) and (22) enhance the LSTM's cells with memory and its hidden states.

$$y_{(b)} = j_{(b)} \bullet y_{(b)} + r_{(b)} \bullet y_{(b)} \quad (21)$$

$$m_{(b)} = s_{(b)} \bullet \tanh(y_{(b)}) \quad (22)$$

The point-wise multiplying procedure for multiple vectors is provided here as $\bullet$.

5.4 Developed AGen-LSTM-based recommendation system

Purpose of AGen-LSTM The developed AGen-LSTM-based recommendation system plays a critical role in enhancing the care and safety of Alzheimer's patients by providing caregivers with real-time, data-driven recommendations. This system is activated when abnormal behaviors are predicted Ab_V^{Pred} in patients through continuous surveillance using 3DARADNet, a deep learning model that analyzes video footage to identify signs of distress or other concerning activities such as wandering, falls, or unusual movements. Once 3DARADNet flags any abnormality, the AGen-LSTM model performs, using its capacity to predict and generate timely recommendations based on the detected behaviors. This integration of advanced AI technologies offers a dynamic solution for patient care, ensuring that interventions are not only reactive but also proactive, reducing potential risks, and improving patient safety. In order to improve

the recommendations, parameters of AGen-LSTM, such as learning rate, batch size, and activation functions, are tuned using RAV-DFA, which improves the recommendation efficiency by increasing the hit rate and MAP.

Novelty and working of AGen-LSTM AGen-LSTM is a powerful variant of the traditional LSTM networks, which are designed to process and predict time-series data. Its ability to understand and forecast patient behavior over time, based on sequences of historical data, makes AGen-LSTM particularly suited for this task. Alzheimer's patients often exhibit behavioral patterns, such as wandering or agitation that can be tracked and predicted by the system. The AGen-LSTM model uses these past behavioral sequences to predict future actions, making it possible to anticipate when a patient might be at risk of an emergency or unsafe behavior. For instance, if the patient has previously shown signs of wandering around a particular time of day or after certain activities, AGen-LSTM can predict that the patient is likely to repeat this behavior shortly. This allows caregivers to be forewarned and prepared to intervene before the situation escalates. The ability of AGen-LSTM to handle time-series data enables it to capture the nuances of each patient's behavioral patterns. As Alzheimer's disease progresses, a patient's behavior and cognitive abilities can fluctuate, making it important for the system to continuously adapt and update its predictions. AGen-LSTM is capable of learning from these changes in real time, ensuring that it remains accurate and relevant even as the patient's condition evolves. The system's adaptability ensures that recommendations are not static but are instead dynamically adjusted based on the patient's latest behavior, providing caregivers with a more personalized and effective approach to care.

Moreover, AGen-LSTM leverages the RAV-DFA to optimize its parameters and fine-tune its learning process. RAV-DFA enhances the model's ability to make more accurate predictions by optimizing key hyperparameters, such as activation function, learning rate, and batch size to improve the mean average precision (MAP) and hit rate, which influence how the network processes past data and generates future predictions. By using RAV-DFA, the AGen-LSTM model can avoid overfitting, improve generalization to new data, and ultimately increase the precision of its recommendations. The use of this optimization technique ensures that the system performs well under various conditions, from different types of patient behavior to the challenges posed by changes in the patient's environment or disease progression. The AGen-LSTM generates real-time recommendations to guide caregivers in their decision-making process. These recommendations can vary based on the specific behaviors identified. For example, if the system detects that a patient is about to wander or leave a safe area, the recommendation might be to increase monitoring or physically intervene to prevent the patient from leaving. If the system identifies signs of agitation or distress, the recommendation could be to calm the patient, ensure their comfort, or assess their health for any underlying issues. Additionally, if the system predicts a likely fall risk based on a sequence of movements, it might alert caregivers to check for hazards in the environment or ensure the patient is safely positioned.

Advantages of AGen-LSTM-based recommendation The real-time nature of the recommendations is crucial for improving patient outcomes and caregiver responsiveness. By providing timely alerts and predictions, the AGen-LSTM-based system allows caregivers to take immediate action, minimizing the chances of adverse events such as falls,

injuries, or emergencies. Furthermore, because the system continuously learns from new data, it becomes increasingly adept at providing more accurate recommendations as it accumulates a broader range of behavioral patterns over time. This learning capability enhances the system's ability to offer proactive care, shifting the focus from simply responding to emergencies to anticipating and preventing them.

Generally, the AGen-LSTM-based recommendation system represents a significant advancement in the care of Alzheimer's patients by integrating predictive analytics with real-time monitoring. Through the detection of abnormal behaviors via 3DARADNet, and the subsequent generation of actionable, personalized recommendations, the system enhances caregiver effectiveness and ensures better patient safety. The ability of AGen-LSTM to adapt to changing behavior patterns, its optimization through RAV-DFA, and its capacity to predict future actions provide caregivers with powerful tools for proactive intervention. By reducing risks, preventing potential emergencies, and improving care efficiency, this recommendation system significantly enhances the quality of care for AD affected individuals and contributes to their overall well-being.

Objective function Eq. (23) offers the objective function for the developed AGen-LSTM-based recommendation system. The main aim of this model is to maximize the MAP and hit rate.

$$OF_3 = \arg \min_{\{Af_D^{LSTM}, Lr_M^{LSTM}, sB_T^{LSTM}\}} (MAP + HitRate) \quad (23)$$

Different terms Af_D^{LSTM} , Lr_M^{LSTM} , and sB_T^{LSTM} represent the activation function, learning rate, and batch size in LSTM in the range of $[1, 5]$, $[0.01, 0.99]$, and $[8, 64]$. The mathematical derivation for MAP MAP and hit rate $HitRate$ has been given in Eq. (24) and Eq. (25).

$$MAP = \frac{\sum (B_{Av})}{p} \quad (24)$$

$$HitRate = \frac{B}{p} \quad (25)$$

here every recommendation's average precision is B_{Av} , the total patients are n , and B refers to the total patients with at least one associated medication prescription.

Figure 6 provides the pictorial architecture of the developed AGen-LSTM-based recommendation system.

6 Results and discussion

6.1 Validation setup

In the proposed AD patient monitoring system, the optimization of parameters was critical for enhancing the performance across different phases: AD detection, abnormality detection, and recommendation generation. Python was used to run the optimization process efficiently across all these phases. In the AD detection phase, the algorithm's population size was fixed as 10, with each chromosome having a length of 3. The maximum number of iterations was fixed at 50. This optimization configuration was designed to fine-tune the parameters of the ADiGRU used for detecting

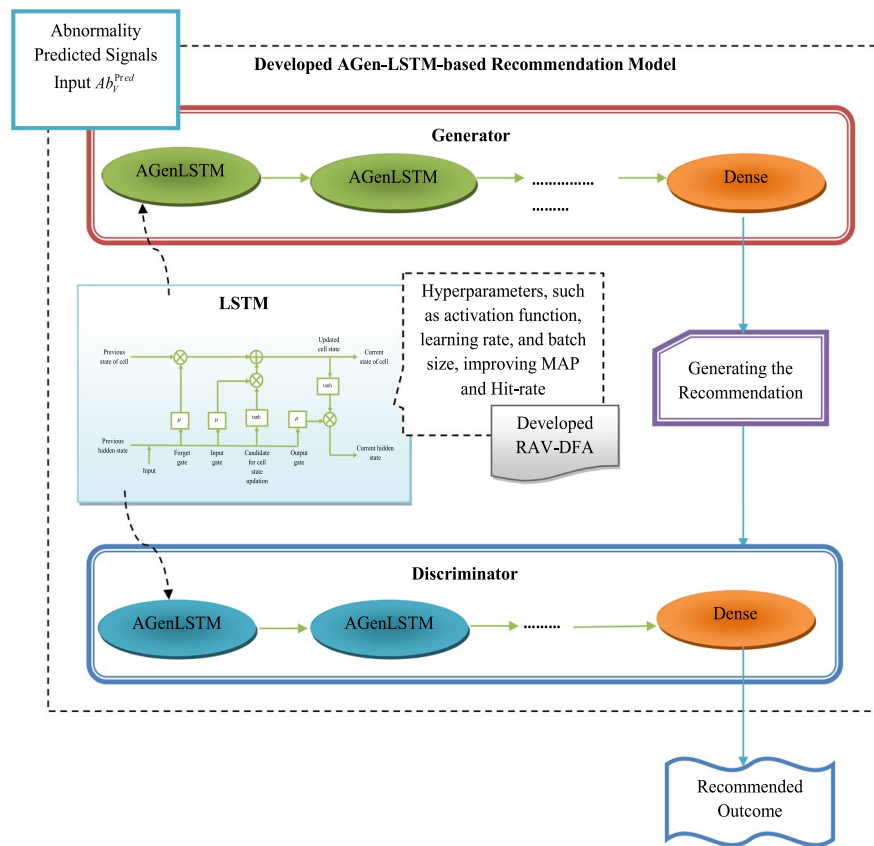


Fig. 6 Pictorial architecture of the developed AGen-LSTM-based recommendation system

AD. Through iterative adjustments, the system aimed to identify the most effective set of parameters to accurately detect AD in patients based on EEG signal features. Similarly, in the abnormality detection phase, the population size remained at 10, with a chromosome length of 3, and a maximum of 50 iterations. This phase involved analyzing video surveillance data from CCTV feeds, where the goal was to identify behavioral abnormalities in AD patients. The optimization process enhanced the accuracy of predictions made by the 3DARADNet, ensuring that any unusual behavior was detected efficiently and promptly. For the recommendation generation phase, the optimization strategy followed the same parameters: a population size of 10, a chromosome length of 3, and a maximum of 50 iterations. This phase was powered by the AGen-LSTM network, which provided actionable recommendations for caregivers or medical professionals based on detected abnormalities. By optimizing the AGen-LSTM parameters through this approach, the system ensured that the generated recommendations were relevant and timely, further improving the overall care provided to AD patients.

Moreover, in the proposed AD patient monitoring system, various networks and optimization algorithms are compared across different phases. For detection comparison, the networks evaluated include DRN-LSTM [1], Bayesian network

[2], CL-ATBiLSTM [6], and DiGRU [30]. In the abnormality detection phase, the networks considered are CNN [5], UNet [33], DenseUNet [34], and RADNet [35]. For the recommendation phase, the networks explored include AdaBoost [7], Kalman filter [4], DWT [6], and Gen-LSTM [32]. Additionally, the optimization algorithms used to enhance performance across these networks include the Artificial Orcas Algorithm (AOA) [36], the American Zebra Optimization Algorithm (AZO) [37], Carpet Weaver Optimization (CWO) [38], and Dark Forest Algorithm (DFA) [29]. These comparisons allow for identifying the most effective combinations of networks and optimization strategies for each phase of the AD monitoring system. The state-of-the-art techniques used in the validation were DRN-LSTM [18], AdaBoost [24], CNN [22], and CNN-GRU [39].

Hardware configurations associated with the developed AD patient monitoring model are given in Table 2.

6.2 Evaluation metrics

This section provides the measures employed in the designed system.

(a) Accuracy:

Table 2 Hardware configurations used in the developed AD patient monitoring model

Software requirements	Anaconda	Version 3
	PyCharm	Version 3.1.1
Hardware requirements	RAM	8 GB
	Version	11
	ROM	500 GB
	Machine	Windows
	Processor	i3
Libraries	Keras, PrettyTable, OpenCV-Python, NumPy, TFLearn, TensorFlow, and Matplotlib	
Parameter settings		
Hyperparameters	Parameter name	Ranges/counts
	Hidden neurons in DiGRU	[5,255]
	Learning rate of DiGRU	[0.01,0.99]
	Steps per epoch of DiGRU	[100,500]
	Activation function in ARADNet	[1,5]
	Learning rate in ARADNet	[0.01,0.99]
	Steps per epoch in ARADNet	[100,500]
	Batch size in ARADNet	[8,64]
Parameters	Epoch in ARADNet	100
	Batch size in ARADNet	32
	Hidden neurons in ARADNet	128
	Optimizer in ARADNet	Sigmoid
	Batch size	32
	Epoch	100
	Activation function	ReLU
	Optimizer	Sigmoid

$$cA = \frac{(Vq + By)}{(Vq + By + Mu + Ak)} \quad (26)$$

(b) The Matthews correlation coefficient (MCC):

$$CmC = \frac{Vq \times By - Mu \times Ak}{\sqrt{(Vq + Mu)(Vq + Ak)(By + Mu)(By + Ak)}} \quad (27)$$

(c) Negative predictive value (NPV):

$$RpV = \frac{Mu}{Ak + Mu} \quad (28)$$

(d) F1 score:

$$E1S = \frac{2 * Vq}{2 * (Vq + Mu + Ak)} \quad (29)$$

(e) False-positive rate (FPR):

$$PeF = \frac{Mu}{Mu + By} \quad (30)$$

(f) Specificity:

$$YsP = \frac{By}{By + Mu} \quad (31)$$

(g) Sensitivity:

$$YeS = \frac{Vq}{Vq + Ak} \quad (32)$$

(h) False discovery rate (FDR):

$$\text{BrF} = \frac{\text{Mu}}{\text{Mu} + \text{Vq}} \quad (33)$$

(i) Dice coefficient:

$$\text{DC} = \frac{2|C \cap D|}{|C| + |D|} \quad (34)$$

Detected outcomes are indicated as C , and ground-truth outcomes are presented as D .

6.3 Cost function evaluation on the proposed RAV-DFA-ADiGRU

The cost function evaluation is given in Fig. 7. This analysis plays a critical role in assessing the performance of a model over different iterations. In the case of RAV-DFA-ADiGRU, the cost function is essential for determining how well the model detects AD by minimizing the error between predicted and actual outcomes. The effectiveness of a model largely depends on how efficiently it reduces this cost, and the RAV-DFA-ADiGRU model stands out by leveraging the RAV-DFA to optimize its parameters. This optimization improves the model's ability to detect AD by refining the learning process, making the model more accurate and efficient. Compared to other optimization algorithms like AOA-ADiGRU, AZO-ADiGRU, CWO-ADiGRU, and DFA-ADiGRU, the RAV-DFA-ADiGRU model proves to be superior in several ways. The AOA-ADiGRU, AZO-ADiGRU, and CWO-ADiGRU, while useful, may struggle with fine-tuning the model parameters as effectively, often leading to slower convergence and higher computational costs.

Similarly, DFA-ADiGRU may offer good performance but lacks the refined tuning capabilities of the RAV-DFA, which improves upon the original DFA by modifying the

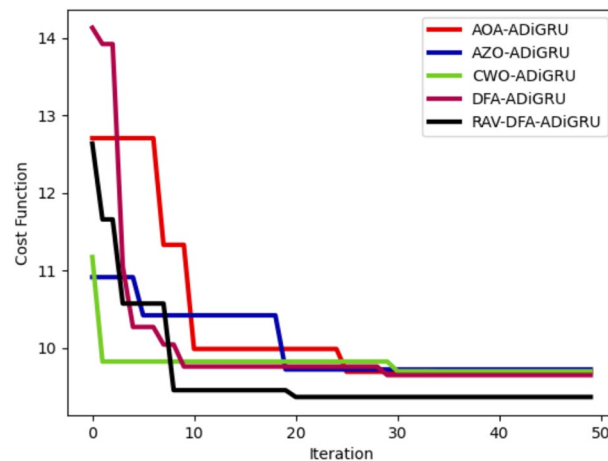


Fig. 7 Cost function evaluation on the proposed system

alpha values, enabling more precise parameter adjustments. This results in RAV-DFA-ADiGRU achieving a lower cost function value faster, with higher accuracy in detecting AD, while consuming fewer computational resources compared to the other methods. In short, the RAV-DFA-ADiGRU model's superior cost function evaluation, stemming from its refined optimization process, makes it more effective, efficient, and accurate in AD detection than AOA-ADiGRU, AZO-ADiGRU, CWO-ADiGRU, and DFA-ADiGRU, proving it to be the better option for real-time monitoring systems.

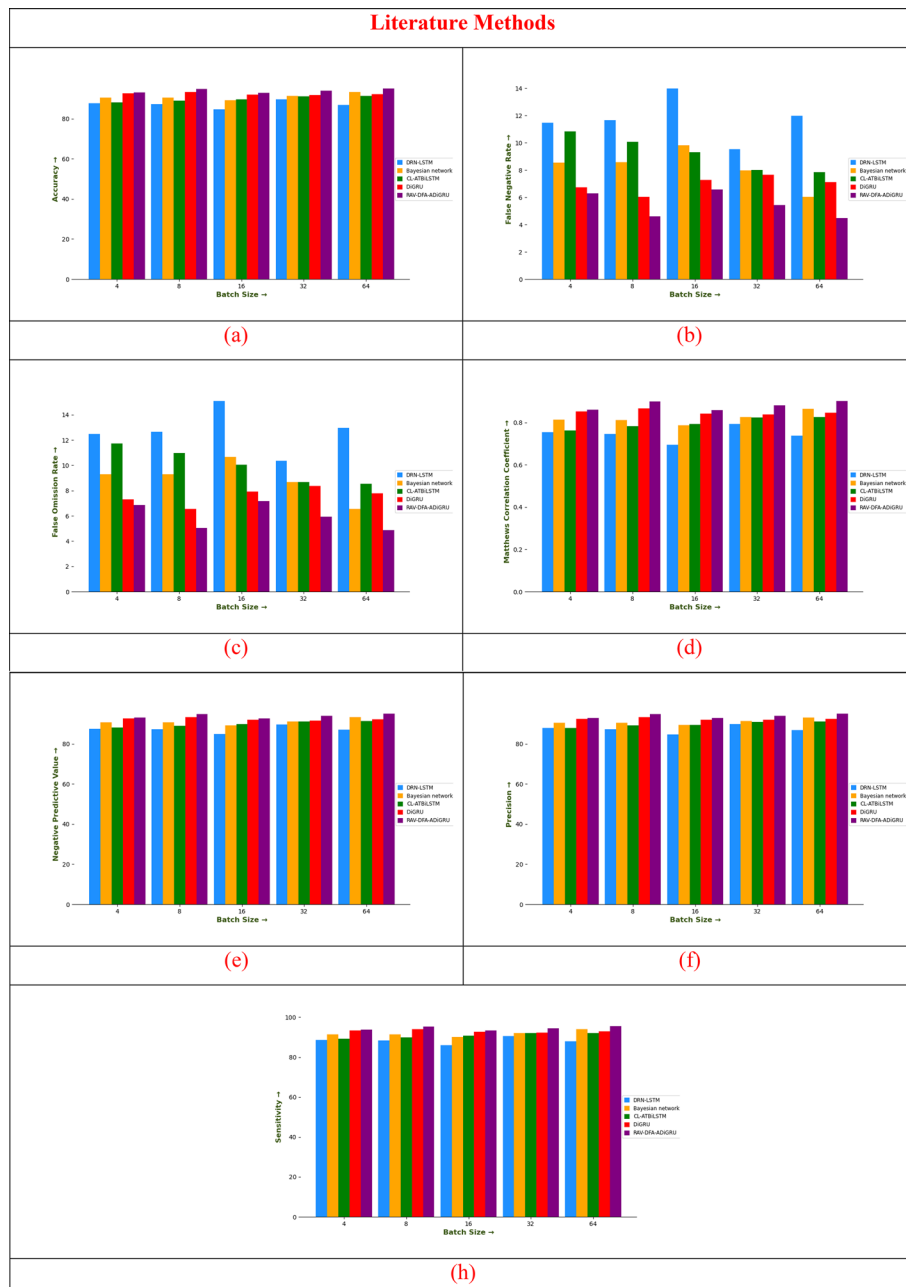


Fig. 8 Batch size analysis in developed RAV-DFA-ADiGRU based on **a** Accuracy, **b** FNR, **c** FOR, **d** MCC, **e** NPV, **f** Precision, and **h** Sensitivity

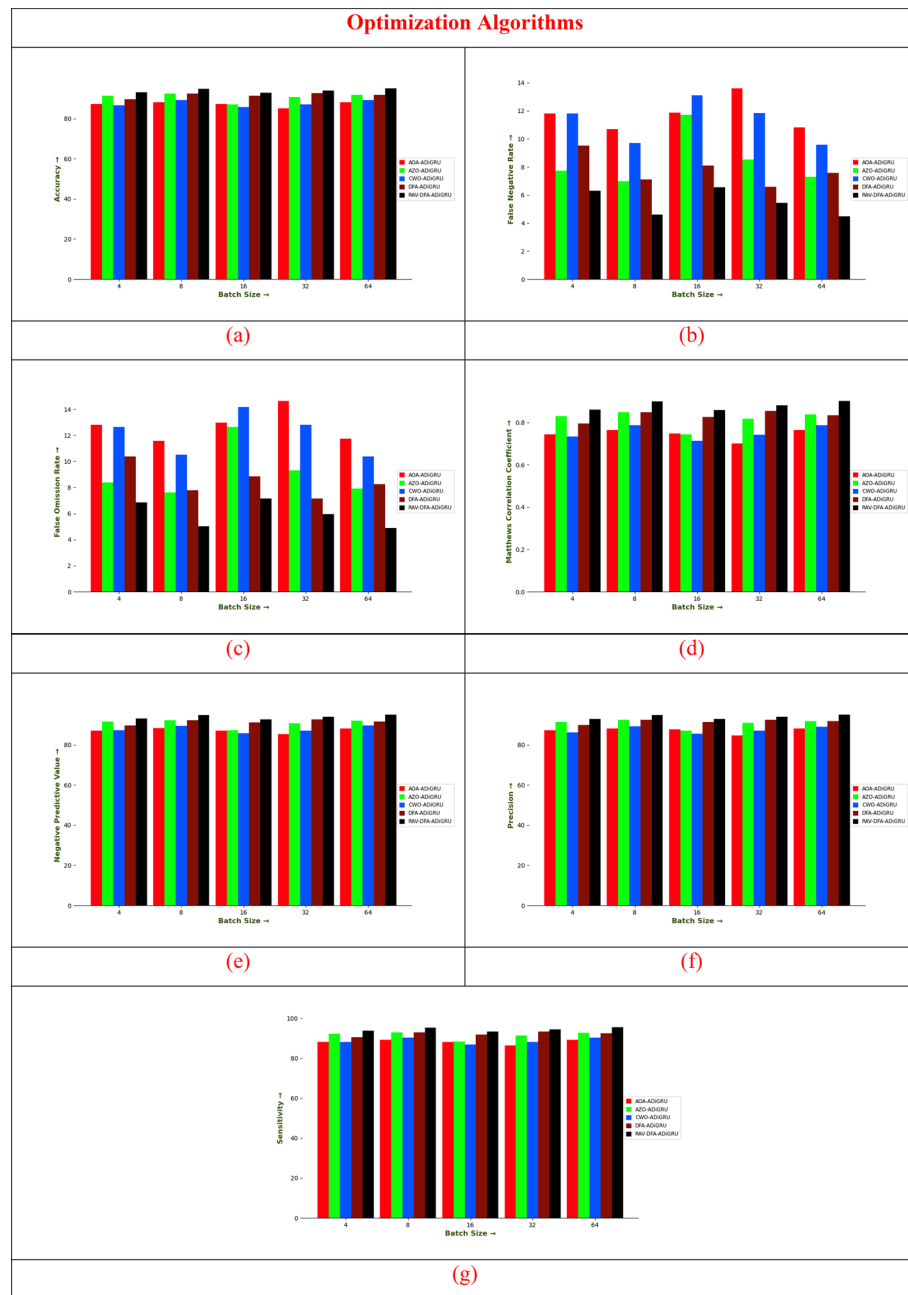


Fig. 8 continued

6.4 ADiGRU-based AD detection evaluation

AD detection computation on the designed RAV-DFA-ADiGRU with existing optimization algorithms and models is given in Fig. 8. This analysis is performed by varying batch sizes. This helps caregivers identify potential issues and offer them actionable insights to provide better support. When comparing the ADiGRU model to other networks like DRN-LSTM, Bayesian networks, and CL-ATBiLSTM, ADiGRU stands out due to its ability to handle both long-term and short-term dependencies with its adaptive dilated gated mechanism. This enables better real-time detection without

the computational overhead seen in models like Bayesian networks or CL-ATBiLSTM, which are more complex and less efficient. Additionally, ADiGRU surpasses models like DiGRU by incorporating a more flexible gating mechanism, allowing it to learn more effectively from evolving data. When compared to optimization algorithms such as AOA-ADiGRU, AZO-ADiGRU, and CWO-ADiGRU, ADiGRU performs well without the need for heavy optimization, ensuring a balance of efficiency and performance in real-time applications. Even though models like RAV-DFA-ADiGRU improve performance by refining the parameters, ADiGRU is still highly effective by itself, offering fast, reliable, and scalable detection for Alzheimer's disease, making it an optimal choice for AD detection systems. Thus, the ADiGRU model proves to be superior to many existing networks and optimization algorithms for AD detection due to its adaptive dilated gated recurrent structure, which allows it to handle long-term dependencies and dynamic changes in patient data effectively. Furthermore, while optimization algorithms like DFA enhance performance, the core strength of ADiGRU lies in its adaptive learning capabilities, which enable it to perform robustly even without heavy reliance on complex optimizers. Therefore, ADiGRU stands out as a highly effective and efficient approach for AD detection, monitoring, and prediction.

6.5 K-fold evaluation on the AD detection model

Tables 3 and 4 show the k -fold evaluation of the AD detection model with existing literature models and optimization algorithms. Performing AD detection-based k -fold evaluation is essential for assessing the model's generalization ability and reliability. This evaluation ensures that the model is computed on various parts of the data, minimizing bias and providing a more accurate estimate of its performance. In the case of the RAV-DFA-ADiGRU model, the k -fold evaluation consistently demonstrates its superiority over other networks and optimization algorithms. Compared to networks like DRN-LSTM, Bayesian network, CL-ATBiLSTM, and DiGRU, RAV-DFA-ADiGRU outperforms them by better handling long-term dependencies and delivering higher accuracy and efficiency. The adaptive dilated gated structure of RAV-DFA-ADiGRU enables it to learn from sequential data more effectively, avoiding the computational overhead seen in the other models. When compared to optimization algorithms like AOA-ADiGRU, AZO-ADiGRU, CWO-ADiGRU, and DFA-ADiGRU, the RAV-DFA-ADiGRU model shines due to its refined optimization process using the RAV-DFA technique, which optimizes parameters faster and more efficiently. The results from the k -fold evaluation clearly demonstrate the superior performance of the RAV-DFA-ADiGRU model compared to other networks and models. For instance, in the first fold, the DRN-LSTM achieved an accuracy of 90.455%, while the Bayesian network scored 92.727%. The CL-ATBiLSTM model achieved an accuracy of 90.182%, and the DiGRU model had a slightly better result at 94.455%. In contrast, the RAV-DFA-ADiGRU model outperformed all others with an accuracy of 96.091%. These results indicate that RAV-DFA-ADiGRU consistently delivers higher accuracy, highlighting its effectiveness in detecting AD compared to other models. The refined optimization process and adaptive dilated gated recurrent structure contribute to its improved performance, making it a highly reliable model for real-time AD detection. This results in lower computational costs and higher detection accuracy. Therefore, the RAV-DFA-ADiGRU model, with its

Table 3 K-fold computation on the AD detection mechanism with existing literature models

Models/k-folds	DRN-LSTM [1]	Bayesian network [2]	CL-ATBiLSTM [6]	DiGRU [30]	RAV-DFA-ADiGRU
<i>Accuracy</i>					
1	90.455	92.727	90.182	94.455	96.091
2	89.727	94.273	92.909	95.818	96.364
3	90.455	93.091	91.636	95.182	96.000
4	88.727	91.364	90.091	93.273	95.636
5	90.636	93.818	91.909	95.909	96.727
<i>Specificity</i>					
1	90.432	92.537	89.483	94.227	95.903
2	89.239	93.878	92.565	95.709	96.269
3	90.130	92.751	91.264	95.140	95.725
4	88.290	90.909	89.758	92.937	95.353
5	90.467	93.494	91.620	95.888	96.642
<i>FPR</i>					
1	9.568	7.463	10.517	5.773	4.097
2	10.761	6.122	7.435	4.291	3.731
3	9.870	7.249	8.736	4.860	4.275
4	11.710	9.091	10.242	7.063	4.647
5	9.533	6.506	8.380	4.112	3.358
<i>NPV</i>					
1	89.925	92.537	90.485	94.403	96.082
2	89.739	94.403	92.910	95.709	96.269
3	90.299	93.097	91.604	94.963	96.082
4	88.619	91.418	89.925	93.284	95.709
5	90.299	93.843	91.791	95.709	96.642
<i>FDR</i>					
1	9.043	7.092	10.106	5.496	3.901
2	10.284	5.851	7.092	4.078	3.546
3	9.397	6.915	8.333	4.610	4.078
4	11.170	8.688	9.752	6.738	4.433
5	9.043	6.206	7.979	3.901	3.191
<i>F1-Score</i>					
1	90.716	92.908	90.374	94.587	96.185
2	89.956	94.400	93.073	95.922	96.454
3	90.683	93.250	91.829	95.306	96.092
4	88.988	91.556	90.328	93.428	95.737
5	90.877	93.961	92.103	96.014	96.809
<i>MCC</i>					
1	0.809	0.854	0.804	0.889	0.922
2	0.794	0.885	0.858	0.916	0.927
3	0.809	0.862	0.833	0.904	0.920
4	0.774	0.827	0.802	0.865	0.913
5	0.813	0.876	0.838	0.918	0.935
<i>FOR</i>					
1	10.075	7.463	9.515	5.597	3.918
2	10.261	5.597	7.090	4.291	3.731
3	9.701	6.903	8.396	5.037	3.918
4	11.381	8.582	10.075	6.716	4.291
5	9.701	6.157	8.209	4.291	3.358

Table 3 (continued)

Models/k-folds	DRN-LSTM [1]	Bayesian network [2]	CL-ATBiLSTM [6]	DiGRU [30]	RAV-DFA-ADiGRU
CSI					
1	83.010	86.755	82.439	89.731	92.650
2	81.745	89.394	87.043	92.164	93.151
3	82.955	87.354	84.893	91.032	92.479
4	80.160	84.426	82.362	87.667	91.823
5	83.279	88.610	85.362	92.334	93.814

enhanced performance and optimization, proves to be the best choice for real-time AD detection, surpassing both existing networks and other optimization algorithms in terms of accuracy, efficiency, and scalability.

6.6 Statistical computation on RAV-DFA-ADiGRU

Statistical validation is displayed in Table 5. Performing this is essential for rigorously assessing the performance of learning schemes, particularly when it comes to critical applications like AD detection. In the context of AD detection, statistical evaluation helps to ensure that the chosen model is not only accurate but also reliable in real-world applications where early diagnosis is crucial. The performance evaluation of various optimization algorithms in the context of AD detection revealed the worst-case performance for different models. The AOA-ADiGRU showed a worst-case performance of 12.708, while the AZO-ADiGRU model achieved a slightly better result with 10.914. The CWO-ADiGRU demonstrated a worst-case performance of 11.176, which is also relatively competitive. In comparison, the DFA-ADiGRU recorded a worst-case performance of 14.136, which was the highest among the models tested. However, the RAV-DFA-ADiGRU model outperformed all other optimization algorithms, with a worst-case performance of 12.639, indicating its superior ability to handle challenging scenarios in AD detection. This evaluation highlights the efficiency and reliability of the RAV-DFA-ADiGRU in comparison with other optimization algorithms. In these evaluations, RAV-DFA-ADiGRU consistently outperformed the other models in all key performance indicators, demonstrating higher accuracy and more reliable detection of AD. The statistical results, therefore, clearly prove that the RAV-DFA-ADiGRU model provides the most efficient and accurate performance, outperforming AOA-ADiGRU, AZO-ADiGRU, CWO-ADiGRU, and DFA-ADiGRU in the detection of AD, making it the most suitable choice for real-time monitoring systems.

6.7 ROC evaluation on RAV-DFA-ADiGRU

ROC computation is given in Fig. 9. Executing the validation is a critical for assessing the effectualness of machine learning models, especially in medical applications like AD detection. The area under the ROC curve serves as a key metric to evaluate the overall performance, where large AUC specifies improved performance. In comparing the RAV-DFA-ADiGRU model to other models such as DRN-LSTM, Bayesian network, CL-ATBiLSTM, and DiGRU, the ROC evaluation highlights the superior capability of RAV-DFA-ADiGRU in accurately identifying AD. While the

Table 4 K-fold evaluation on the ad detection model with prior optimization algorithms

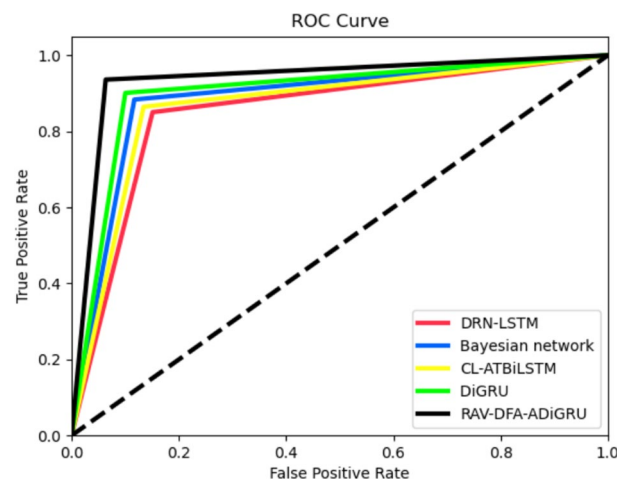
Optimization algorithms/k-fold	AOA-ADiGRU [36]	AZO-ADiGRU [37]	CWO-ADiGRU [38]	DFA-ADiGRU (Li et al. 2023)	RAV-DFA-ADiGRU
<i>Accuracy</i>					
1	88.636	91.909	91.000	93.545	96.091
2	89.818	92.545	91.727	94.091	96.364
3	89.636	93.182	91.636	94.636	96.000
4	88.000	92.000	90.000	92.364	95.636
5	90.455	93.273	92.455	94.636	96.727
<i>Specificity</i>					
1	87.985	91.466	90.239	93.458	95.903
2	89.552	92.351	91.280	93.855	96.269
3	89.219	92.764	90.809	94.085	95.725
4	87.546	91.636	89.591	92.322	95.353
5	89.834	92.778	92.179	94.413	96.642
<i>FPR</i>					
1	12.015	8.534	9.761	6.542	4.097
2	10.448	7.649	8.720	6.145	3.731
3	10.781	7.236	9.191	5.915	4.275
4	12.454	8.364	10.409	7.678	4.647
5	10.166	7.222	7.821	5.587	3.358
<i>NPV</i>					
1	88.806	91.978	91.418	93.284	96.082
2	89.552	92.351	91.791	94.030	96.269
3	89.552	93.284	92.164	94.963	96.082
4	87.873	91.978	89.925	91.978	95.709
5	90.672	93.470	92.351	94.590	96.642
<i>FDR</i>					
1	11.525	8.156	9.397	6.206	3.901
2	9.929	7.270	8.333	5.851	3.546
3	10.284	6.915	8.865	5.674	4.078
4	11.879	7.979	9.929	7.270	4.433
5	9.752	6.915	7.447	5.319	3.191
<i>F1-Score</i>					
1	88.869	92.089	91.169	93.711	96.185
2	90.071	92.730	91.911	94.232	96.454
3	89.876	93.333	91.786	94.746	96.092
4	88.277	92.185	90.231	92.566	95.737
5	90.650	93.416	92.635	94.765	96.809
<i>MCC</i>					
1	0.773	0.838	0.820	0.871	0.922
2	0.796	0.851	0.834	0.882	0.927
3	0.793	0.864	0.833	0.893	0.920
4	0.760	0.840	0.800	0.847	0.913
5	0.809	0.865	0.849	0.893	0.935
<i>FOR</i>					
1	11.194	8.022	8.582	6.716	3.918
2	10.448	7.649	8.209	5.970	3.731
3	10.448	6.716	7.836	5.037	3.918
4	12.127	8.022	10.075	8.022	4.291
5	9.328	6.530	7.649	5.410	3.358

Table 4 (continued)

Optimization algorithms/k-fold	AOA-ADiGRU [36]	AZO-ADiGRU [37]	CWO-ADiGRU [38]	DFA-ADiGRU (Li et al. 2023)	RAV-DFA-ADiGRU
CSI					
1	79.968	85.338	83.770	88.167	92.650
2	81.935	86.446	85.033	89.094	93.151
3	81.613	87.500	84.818	90.017	92.479
4	79.014	85.502	82.201	86.161	91.823
5	82.899	87.646	86.281	90.051	93.814

Table 5 Statistical evaluation on the AD detection model

Terms	AOA-ADiGRU [36]	AZO-ADiGRU [37]	CWO-ADiGRU [38]	DFA-ADiGRU [29]	RAV-DFA-ADiGRU
Worst	12.708	10.914	11.176	14.136	12.639
Best	9.691	9.721	9.697	9.648	9.364
Mean	10.300	10.036	9.800	10.034	9.664
Median	9.838	9.721	9.823	9.758	9.364
Standard deviation	1.045	0.425	0.206	1.029	0.695

**Fig. 9** ROC evaluation on the developed model

DRN-LSTM and Bayesian network models show moderate AUC scores, they struggle with capturing the complex patterns in AD data, leading to a lower true-positive rate and higher FPR. The CL-ATBiLSTM model, despite its bidirectional LSTM structure, faces difficulties in handling long-range dependencies, which impacts its ability to accurately classify AD. The DiGRU model, while effective in some cases, does not provide the same level of refinement and optimization that RAV-DFA-ADiGRU achieves. Through its RAV-DFA optimization, RAV-DFA-ADiGRU significantly improves AUC, achieving a higher true-positive rate and a lower FPR. This makes it the most reliable model for early and accurate AD detection, as proven by its superior ROC performance compared to the other networks. The higher AUC and better



Fig. 10 Analysis on RAV-DFA-3DARADNet regarding **a** Accuracy, **b** Dice Coefficient, **c** IoU, **d** MSE, **e** Precision, **f** Recall, and **g** Specificity

overall ROC characteristics of RAV-DFA-ADiGRU demonstrate its effectiveness in real-world applications where accurate diagnosis is crucial.

6.8 3DARADNet-based abnormality detection evaluation

Abnormality detection-based evaluation on the designed RAV-DFA-3DARADNet is provided in Fig. 10 by varying statistical measures. This evaluation is crucial for assessing the effectiveness of models in identifying specific, often subtle, abnormalities in medical

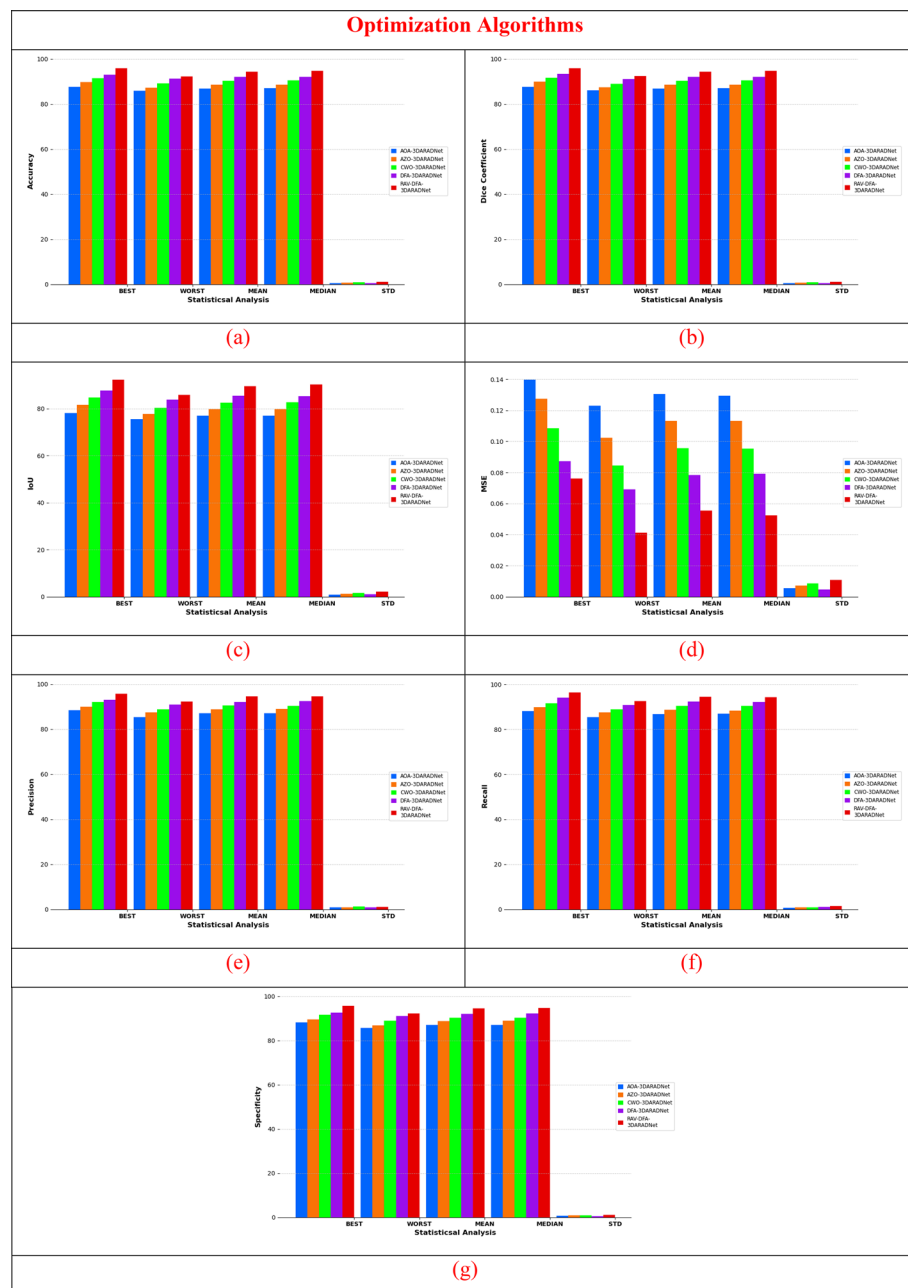


Fig. 10 continued

data, such as the early signs of AD. Abnormality detection focuses on detecting unusual patterns or deviations from normality, which are effective in diagnosing conditions like AD at an early stage. Evaluating models based on their ability to accurately identify these abnormalities helps in understanding their sensitivity and robustness, especially when working with complex, noisy data. When comparing the developed RAV-DFA-3DARADNet model to other networks, such as CNN, UNet, DenseUNet, and RADNet, as well as optimization algorithms like AOA-3DARADNet, AZO-3DARADNet, CWO-3DARADNet, and DFA-3DARADNet, it becomes evident that RAV-DFA-3DARADNet

outperforms these models in abnormality detection. While CNN, UNet, DenseUNet, and RADNet models are capable of detecting abnormalities, they lack advanced optimization techniques that enhance detection performance. The RAV-DFA-3DARADNet model, with its integration with the RAV-DFA, can fine-tune the parameters more efficiently, leading to better detection of subtle abnormalities and achieving higher sensitivity and precision in identifying Alzheimer-related changes. This results in fewer false positives and negatives and makes the developed RAV-DFA-3DARADNet more reliable choice for abnormality detection in AD applications, ultimately proving it to be superior to the other networks and optimization algorithms in this task.

6.9 AGen-LSTM-based AD recommendation evaluation

AD recommendation-based evaluation is given in Fig. 11. Performing this assessment is essential for assessing the effectiveness of models in providing actionable recommendations for AD patients and caregivers. In this context, recommendation-based evaluation focuses on how well the model can suggest suitable interventions, activities, or treatments based on the data collected from patients. This evaluation typically examines how accurately and timely the system generates suggestions that are both relevant and helpful for the specific needs of AD patients. When comparing the developed RAV-DFA-AGen-LSTM model to other networks, such as AdaBoost, Kalman filter, DWT, and Gen-LSTM, and optimization algorithms like AOA-AGen-LSTM, AZO-AGen-LSTM, CWO-AGen-LSTM, and DFA-AGen-LSTM, the RAV-DFA-AGen-LSTM model consistently proves to be superior. While AdaBoost, Kalman filter, and DWT are well-established models, they cannot handle the sequential and temporal nature

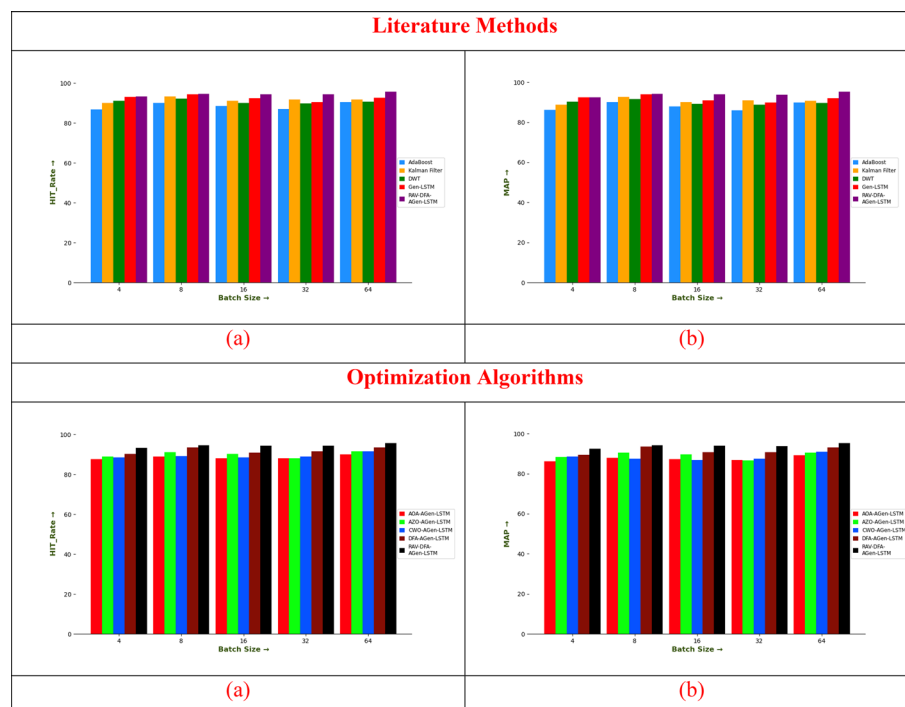


Fig. 11 AD Recommendation-based evaluation on designed RAV-DFA-AGen-LSTM based on **a** Hit Rate and **b** MAP

of AD data, which is crucial for making personalized and dynamic recommendations. The Gen-LSTM model, although effective for sequential data, does not incorporate the refined optimization techniques that RAV-DFA offers. The RAV-DFA-AGen-LSTM model benefits from the refined alpha-based optimization through RAV-DFA, allowing for improved performance in recommendation generation. By enhancing the optimization of LSTM parameters, RAV-DFA-AGen-LSTM can more accurately predict the needs of AD patients and generate personalized recommendations, leading to better outcomes. When compared to optimization algorithms like AOA-AGen-LSTM, AZO-AGen-LSTM, CWO-AGen-LSTM, and DFA-AGen-LSTM, the RAV-DFA-AGen-LSTM outperforms them by providing faster convergence, higher prediction accuracy, and more relevant suggestions, thus improving the quality of care for AD patients. The superior recommendation generation capability of RAV-DFA-AGen-LSTM makes it the most effective choice for AD recommendation systems, surpassing other models and optimization algorithms in terms of both accuracy and real-time applicability.

Table 6 Comparative results on designed RAV-DFA-ADiGRU with state-of-the-art networks

Models/k-folds	DRN-LSTM [18]	AdaBoost [24]	CNN [22]	CNN-GRU [39]	RAV-DFA-ADiGRU
<i>Accuracy</i>					
1	88.182	90.455	89.818	94.455	96.091
2	87.636	91.091	91.091	95.818	96.364
3	88	90.727	90.455	95.182	96
4	86.818	89.636	89.818	93.273	95.636
5	88.091	91.182	90.364	95.909	96.727
<i>Specificity</i>					
1	87.95	90.182	88.91	94.227	95.903
2	86.727	91.364	90.182	95.709	96.269
3	87.455	90.91	89.636	95.14	95.725
4	85.91	88.818	88.91	92.937	95.353
5	87.636	91.091	90.091	95.888	96.642
<i>FPR</i>					
1	11.045	9.818	10.91	5.773	4.097
2	12.273	8.636	8.91	4.291	3.731
3	11	9.091	9.545	4.86	4.275
4	13.182	10.182	11.09	7.063	4.647
5	11.364	8.909	9.636	4.112	3.358
<i>NPV</i>					
1	87.091	90.182	89.091	94.403	96.082
2	86.909	91.182	91.091	95.709	96.269
3	87.364	90.727	90.455	94.963	96.082
4	85.636	89.091	88.91	93.284	95.709
5	87.364	91.364	90.091	95.709	96.642
<i>FDR</i>					
1	12.05	9.818	10.91	5.496	3.901
2	13.273	8.636	8.91	4.078	3.546
3	12	9.091	9.545	4.61	4.078
4	14.182	10.182	11.09	6.738	4.433
5	12.364	8.909	9.636	3.901	3.191

6.10 State-of-the-art validation

Table 6 shows the performance analysis of proposed AD identification model compared with other existing works. This analysis is made up with different measures by varying the different k -folds. In the accuracy validation, the developed RAV-DFA-ADiGRU model achieves a higher AD detection efficiency as 9.8% higher than DRN-LSTM, 6.08% higher than AdaBoost, 7.04% efficient than CNN, and 0.85% improved CNN-GRU model, while considering the k -fold value as 5. The analysis outcomes displayed that the suggested RAV-DFA-ADiGRU is good in achieving better accuracy in complex classes. DRN-LSTM [18] is efficient in tackling the gradient issues, but it needs more memory space for the validation. Moreover, it takes more time to process the samples and is also not suitable to use in all kinds of environment. AdaBoost [24] is efficient in reducing the overfitting issues and also maintains higher flexibility in different classes. However, processing the sequential information leads to misclassifications and prone to more errors in the outcomes. CNN-GRU [39] is good in processing the temporal and spatial features. But computational complexity of the network is higher, and also maintaining the interpretability is challenging. Here, improved accuracy is accomplished by the developed RAV-DFA-ADiGRU by using the noise free and relevant samples at the training phase, which supports to accomplish the reliable outcomes. Moreover, the ADiGRU is efficient in collecting the longer-range dependencies and also tackles the vanishing gradient issues, which helps the developed network to gain more precise outcomes in the dynamic environment. Using the novel optimization scheme RAV-DFA in the network ADiGRU aids to improve the overall robustness and also achieve higher AD detected outcomes. The developed RAV-DFA-ADiGRU is good in reducing the computational complexity with proper parameters tuning. In the error analysis, the developed RAV-DFA-ADiGRU is good at reducing errors and obtains more AD detection outcomes. Reducing the errors helps to speed up the training and quickly detect the AD without any misclassifications. Henceforth, a high set of results is obtained that can declare the high efficiency of the disease diagnosis model to easily and effectively.

6.11 Runtime analysis

Table 7 demonstrates the runtime analysis carried out in the developed RAV-DFA-3DARADNet-based AD patient monitoring model over the classical models. Executing the runtime validation in the developed RAV-DFA-3DARADNet supports verifying the overall network efficiency and scalability. The analysis outcomes displayed that the developed RAV-DFA-3DARADNet gained a reduced runtime than the classical techniques in predicting the AD among the individuals. In the runtime analysis, the

Table 7 Runtime analysis on proposed RAV-DFA-3DARADNet-based AD patient monitoring model

Algorithm	Time (mins)
AOA-3DARADNet [36]	22.4
AZO-3DARADNet [37]	23.9
CWO-3DARADNet [38]	22.38
DFA-3DARADNet [29]	21.74
Developed RAV-DFA-3DARADNet	20.54

developed RAV-DFA-3DARADNet use a minimal runtime as 20.54 (mins) than the other techniques like AOA-3DARADNet, AZO-3DARADNet, CWO-3DARADNet, and DFA-3DARADNet, respectively. Here, AZO-3DARADNet uses a higher runtime as 23.9 (mins) to process the data samples. Finally, the analysis outcomes displayed that the recommended RAV-DFA-3DARADNet is good at obtaining better decisions by tackling the validation issues and errors.

6.12 Computational complexity analysis

Computational complexity analysis carried out in the developed AD patient monitoring is represented in Table 8. This validation enhances real-time decision-making by processing the samples quickly. Here, the term n displays the length of the sequence, h represents the hidden units, d signifies the feature dimensions, K indicates the size of the convolution kernel, H specifies the heights of input feature maps, and W highlights the width of the input feature maps. Moreover, the outcome channels are indicated as C_{ot} , input channels are specified as C_{in} , tree width in the Bayesian network is highlighted as w , epoch is given as Ep , counts of the used samples are given as N , and asymptotic computational complexity for the dominant operation is indicated as $O()$ in the equations below. DRN-LSTM is expensive due to the presence of convolution layers. In the DiGRU model, dilation is increased due to the presence of receptive fields. Finally, the developed RAV-DFA-ADiGRU is good at reducing the epoch counts and also speeds up the training efficiency.

7 Conclusion

The proposed AD patient monitoring system utilized deep learning techniques to provide an efficient and comprehensive solution for the early detection and continuous monitoring of AD. By integrating EEG signal analysis with the ADiGRU for accurate detection, optimized through the RAV-DFA, the system significantly improved performance in identifying AD patients. The incorporation of surveillance video analysis using 3DARADNet further enhanced its ability to detect abnormalities in real time. Additionally, AGen-LSTM was employed to generate timely and relevant recommendations for caregivers, supporting better patient care management. Optimized with RAV-DFA, the system demonstrated superior performance compared to existing models, offering a reliable and scalable solution for AD monitoring. The evaluation of optimization algorithms using k -fold cross-validation revealed significant differences in accuracy across the models. AOA-ADiGRU achieved an accuracy of 88.636%, while AZO-ADiGRU performed slightly better with an accuracy of 91.909%.

Table 8 Computational complexity validation on classifiers

Classifiers	Computational complexity
Bayesian network [2]	$O(\exp(w))$
DRN-LSTM [1]	$O(K^2 \cdot H \cdot W \cdot C_{in} \cdot C_{ot}) + O(n \cdot h^2)$
DiGRU [30]	$O(n \cdot h^2)$
CL-ATBiLSTM [6]	$O(K^2 \cdot H \cdot W \cdot C_{in} \cdot C_{ot}) + O(n^2 \cdot d) + O(n \cdot h^2)$
Developed RAV-DFA-ADiGRU	$O(n \cdot h^2)(Ep)$

CWO-ADiGRU followed closely with an accuracy of 91.000%, indicating a relatively strong performance. DFA-ADiGRU showed a higher accuracy of 93.545%, reflecting its improved optimization. However, the RAV-DFA-ADiGRU model demonstrated the highest accuracy, reaching 96.091%, outperforming all other optimization algorithms. This demonstrates the superior performance of RAV-DFA-ADiGRU in AD detection, highlighting its effectiveness in achieving higher accuracy in comparison with the other models tested. The developed model provided early AD detection, enhanced accuracy through ADiGRU and 3DARADNet, optimized performance with RAV-DFA, and personalized recommendations for caregivers. The system is scalable for real-time monitoring, making it highly effective for AD management. It also allows for noninvasive monitoring through EEG and video surveillance, reducing the need for constant in-person checkups. The continuous learning ability of the system allows it to adapt and improve over time as more data are collected. Additionally, the system's ability to analyze both physiological and behavioral data provides a holistic view of the patient's condition, which can lead to better-tailored care.

7.1 Limitations and future scope

However, some limitations include the dependency on quality EEG datasets, privacy concerns with CCTV surveillance, the need for significant computational power, and potential challenges in generalizing across diverse patient populations. Moreover, the integration of multiple complex models might lead to higher implementation costs. Future scope includes expanding the system to integrate additional biomarkers for more comprehensive monitoring, enhancing privacy and security, creating lightweight versions for resource-limited settings, and exploring broader healthcare applications. Long-term clinical trials will also help refine the system's effectiveness and applicability in real-world scenarios.

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Author contributions

Revathi Mohan, and Premkumar Borugadda: Conceptualization, Methodology, Software Data curation, Writing—Original draft preparation, Reviewing and Editing, Software Validation. Nageshwar Rao Lavuri and Sumanth Venugopal: Formal Analysis, Investigation, Methodology, Project Administration, Resources, Software, Supervision, Validation, Visualization.

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Data availability

The developed AD patient monitoring system uses the required EEG signals from the standard resources, and its details are given as follows. Here, essential EEG signals are sourced from Computational methods of EEG signals analysis for AD classification dataset and the EEG signals are collected from the link "<https://osf.io/2v5md/overview>": Access Date 2025–12-09. Moreover, the abnormality detection procedures are carried out in the developed AD detection model by considering the CCTV footage. Here, the samples used for abnormality detection are sourced from the benchmark dataset named Human Activity Recognition-Fall-Up dataset, and the required samples are collected from the link "<https://sites.google.com/up.edu.mx/har-up/>": Access Date 2025–12-09". Next, the collected video samples are processed using 3DARADNet to detect the abnormalities.

Declarations

Ethical approval and consent to participate

Not applicable.

Informed consent

Not applicable.

Consent for publication

Not applicable.

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Competing interest

The authors declare no competing interests.

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