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Elderly Healthcare Using Federated Learning Approach

Arul Antran Vijay S.[1,*], Jebson J.[2], Subairkhan A.[2], Vasanthakumar R.[2], Vinith Kumar V.[2]

Abstract

The healthcare system for elderly people faces several challenges, which can be addressed using advanced machine learning models. These models can help monitor chronic diseases, detect falls, and provide personalized health recommendations. The study uses comprehensive datasets like MIMIC-III/IV, WESAD, and UCIHAR to explore human movements, device limitations, and the differences in fall occurrences. A detailed review of existing literature discusses current technologies for activity monitoring and fall detection, focusing on deep learning methods like convolutional neural networks (CNNs) for detecting unusual patterns, recurrent neural networks (RNNs) and long short-term memory (LSTM) architectures are employed to analyze sequential data, while deep reinforcement learning (DRL) is utilized to enhance the personalization of treatment strategies. The approach integrates federated learning to maintain patient data confidentiality, which is crucial in healthcare settings. The effectiveness of the models is assessed using evaluation metrics including accuracy, precision, recall, and F1-score, offering insights into their performance advantages and limitations. A comparison of different models provides valuable insights into their performance and relevance in clinical settings. The findings highlight how these technologies could improve outcomes for patients in critical care, with future research aimed at making the models more accurate and widely applicable for elderly health management.

Keywords: Long short-term memory, recurrent neural network, convolutional neural network, deep reinforcement learning, WESAD, UCI HAR, MIMIC III, Internet of Medical Things

INTRODUCTION

The elderly healthcare system leverages artificial intelligence, the Internet of Things (IoT), and advanced health monitoring technologies to enhance the quality of life of senior citizens. It incorporates wearable devices such as fitness trackers and smartwatches to continuously monitor vital health parameters, including heart rate, blood pressure, oxygen saturation, body temperature, and Electrocardiogram (ECG) in real time. These devices also monitor daily activities such as steps, calories, and sleep, offering insights into overall wellness. Additionally, smart sensors placed in high-risk areas, such as bedrooms, bathrooms, and kitchens, can detect changes in behavior or emergencies, such as falls or unusual inactivity. Bedroom sensors track sleep quality and disruptions, whereas kitchen and bathroom sensors ensure safety by detecting injuries. In case of emergencies, alerts are sent to family members or healthcare providers. Artificial intelligence and machine learning have been used to forecast health patterns and provide tailored suggestions to enhance both safety and quality of care. The system promotes independence for seniors while providing peace of mind for caregivers. Overall, it enhances the safety, health, and self-sufficiency of elderly individuals.

***Author for Correspondence**
Arul Antran Vijay S.
E-mail: arulantranvijay@gmail.com

[1]Associate Professor, Department of Computer Science and Engineering, Karpagam College of Engineering, Coimbatore, Tamil Nadu, India
[2]Student, Department of Computer Science and Engineering, Karpagam College of Engineering, Coimbatore, Tamil Nadu, India

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Background History

The global shift towards an aging population presents significant challenges for healthcare, as the elderly are more susceptible to chronic diseases, falls, and cognitive decline, necessitating proactive and efficient solutions. Deep learning, a branch of artificial intelligence, holds significant promise in tackling challenges in elderly care through predictive analytics and data-driven insights. By emulating the manner in which the human brain processes information, deep learning employs neural networks to examine large datasets and identify patterns and irregularities essential for monitoring senior health. This technology plays a crucial role in spotting subtle changes in health that may have serious implications. With its ability to manage complex and high-dimensional information, deep learning is revolutionizing healthcare. Its use in elderly care includes early diagnosis of diseases and the development of customized treatment strategies, ultimately transforming the way health services support the aging population [1–3].

Problem Statement

The elderly face health challenges such as chronic diseases, fall risks, and conditions such as Alzheimer’s, which require accurate and personalized care. Addressing these issues involves analyzing diverse healthcare data, from wearable sensor time-series data to high-resolution medical images such as MRIs. Deep learning models, such as long short-term memory (LSTM), convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep reinforcement learning (DRL), offer unique strengths for such tasks. LSTMs are ideal for time-series data, CNNs excel in image analysis, RNNs handle sequential data, and DRL optimizes the treatment strategies. Each model’s performance depends on the task and data type, which requires careful selection for effective elderly healthcare solutions [4–7].

RELATED WORKS

Comparative Analysis for Fall Detection

Evaluating fall detection models for elderly care involves analyzing their precision, response times, sensitivity, and false alarm rates using sensor data, such as accelerometers and gyroscopes. The focus is on determining which model, among CNN, RNN, and LSTM, offers the best balance between accurate detection and minimal false positives. Models were assessed for timely responses and reliable sensitivity to detect diverse fall types while avoiding unnecessary alerts. Achieving the right balance significantly improves the safety and autonomy of older adults [8–11]. The goal is to identify a model that maximizes accuracy and reliability by addressing the critical challenges of variability and device constraints.

Diagnostic Accuracy in Alzheimer’s Disease

Deep learning models, particularly CNNs and RNNs, are highly effective in diagnosing Alzheimer’s disease using medical imaging, such as MRI scans and cognitive assessment data. CNNs excel at extracting spatial features from imaging data, enabling the identification of early signs, whereas RNNs capture temporal patterns, supporting the tracking of disease progression. Comparing these models highlights their respective strengths: CNNs in pinpointing structural brain changes and RNNs in analyzing sequential cognitive assessments [12–16]. An optimal approach may involve combining these capabilities to improve early diagnosis and comprehensive monitoring. This enhances timely intervention and supports personalized treatment strategies.

Challenges and Emerging Trends

The implementation of federated learning for fall detection in elderly healthcare presents several challenges. The variability in fall patterns among individuals makes it difficult to generalize models across diverse datasets. Device constraints, such as limited battery life and computational power in wearable sensors, restrict the real-time processing capabilities [17–21]. Ensuring data privacy and security during decentralized model training adds to the complexity, particularly when dealing with sensitive health information. Achieving a high model accuracy while minimizing false positives and negatives remains critical for reliable fall detection. Communication latency and synchronization between devices can affect the efficiency of federated learning. Additionally, balancing the data heterogeneity across users and integrating multimodal sensor data further complicates the model optimization. Addressing these challenges is crucial for delivering effective and robust fall detection solutions for elderly care [22, 23].

Research Objective

This project aimed to bridge the gap between advanced deep learning techniques and real-world healthcare applications for the elderly, ensuring that technology enhances patient outcomes. The system will operate with continuous learning and adaptation, using real-time sensors and imaging data to identify potential health risks early and help prevent severe medical conditions. Furthermore, the initiative emphasizes personalized care by customizing interventions to match each person's specific health needs, thereby enhancing their overall quality of life. Collaboration with healthcare professionals and domain experts is crucial to ensure that the system meets clinical standards and is practical for real-world implementations.

METHODOLOGY

The methodology for elderly healthcare, including fall detection using MIMIC III, WESAD, and UCI HAR, involves several key steps, including the integration of wearable devices, environmental sensors, and AI algorithms for a comprehensive health monitoring system (Figure 1).

Wearables such as smartwatches track vital signs such as heart rate and ECG, whereas environmental sensors detect falls and monitor sleep in high-risk areas. IoT transmits these data to AI models, such as CNNs, RNNs, and LSTMs, for analysis and anomaly detection. Alerts were sent to caregivers during emergencies to ensure timely intervention.

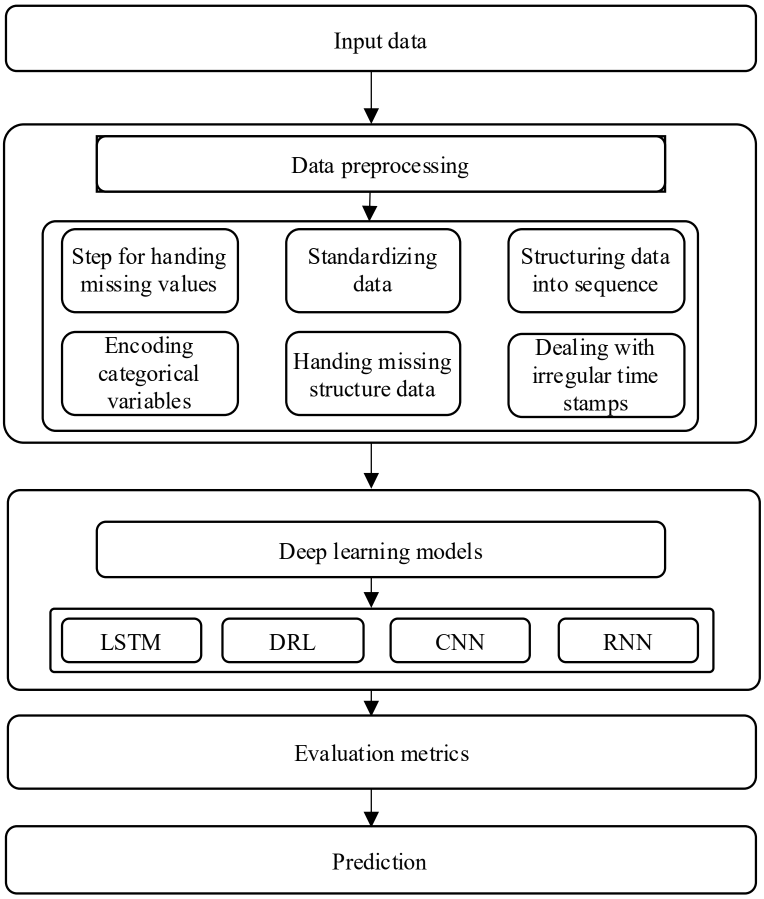

Figure 1. Proposed workflow.

Data Collection

The elderly healthcare system uses wearables, smart sensors, and AI to monitor and analyze health data in real time. It leveraged the MIMIC dataset with de-identified Intensive Care Unit (ICU) records to simulate real-world scenarios. Wearables track vital signs, whereas sensors detect falls, monitor sleep, and ensure safety. AI processes data to detect risks, provides personalized insights, and enhances care. The system ensures privacy through compliance with Health Insurance Portability and Accountability Act (HIPAA) and General Data Protection Regulation (GDPR), thereby improving seniors' health, safety, and independence (Table 1).

Preprocessing

Data preprocessing is an essential step in developing a fall detection system using federated learning with the MIMIC III/IV, WESAD, and UCI HAR datasets. Initially, data cleaning was performed to handle missing values and remove noise. For WESAD and UCI HAR, sensor signals, such as accelerometer and gyroscope data, were segmented into fixed windows to capture temporal patterns. MIMIC-III/IV data were pre-processed by normalizing physiological parameters and encoding categorical features. Feature extraction is applied to derive meaningful metrics, such as motion intensity and statistical features. Standardization and normalization ensure compatibility across the datasets. The data were then partitioned by users to maintain privacy and enable federated learning. This pipeline ensures high-quality data for the training of accurate and reliable models.

Proposed Approach

The elderly healthcare system using federated learning for fall detection can be enhanced through the integration of powerful machine learning algorithms, such as CNN, RNN, LSTM, and DRL. CNNs are particularly useful for processing spatial data from wearables and environmental sensors, enabling the system to detect abnormal movement patterns or falls based on visual data or sensor output. By extracting meaningful features from these data streams, CNNs can accurately identify signs of a fall.

RNNs are effective in handling sequential data, analyzing time-series signals from motion sensors or wearables to detect abnormal patterns in the user’s movement, and identifying potential falls or risky behaviors. LSTM, a variant of RNN, is well-suited for capturing long-term dependencies in movement sequences, allowing the system to learn complex temporal patterns and predict falls before they occur based on past activity.

LSTM for Sequential Data

Step 1. Load the Dataset

Load the input features (X) and target labels (y) from the dataset and return the input features and target labels for further processing.

Step 2. Preprocess the Data

The input features are normalized or standardized to ensure they are on a similar scale, and the input data are reshaped to the required format for the LSTM input ([samples, timesteps, features]). The pre-processed input features are returned.

Table 1. Dataset classification.

Dataset	Data types	Healthcare application	Sample size
MIMIC III/IV	Time-series data, clinical data, and textual data	Mortality prediction, chronic disease monitoring, ICU management, and critical care	MIMIC-III: 53,000+ ICU admissions MIMIC-IV: 70,000+ ICU admissions
WESAD	Sensor data, time-series data	Emotion and stress recognition, mental health monitoring, stress management for the elderly	15 subjects (6 different activities)
UCI HAR	Sensor data, time-series data	Daily activity recognition, fall detection, and mobility assessment for the elderly	30 subjects, 10,299 samples (6 activity classes)

Step 3. Load and Preprocess the Data

The dataset is loaded by retrieving the input features and target labels, preprocessing the input features by normalizing and reshaping them, splitting the dataset into training and testing sets, and returning the training and testing data.

Step 4. Create the LSTM Model

A sequential model is initialized by adding the first LSTM layer with a specific number of units and set return sequences, adding a dropout layer to prevent overfitting, adding a second LSTM layer with a different number of units, setting return sequences to false, adding another dropout layer for further regularization, adding a dense layer with an appropriate number of units and activation function, adding a final dropout layer for regularization, adding the final dense layer with one unit, and activating the output.

RNN for Sequential Data

Step 1. Load the Dataset

Import and load the dataset containing input features (X) and target labels (y).

Step 2. Preprocess the Data

Normalize or standardize input features (X). The features are reshaped to be compatible with the RNN input format.

Step 3. Load and Preprocess the Data

Load the dataset by calling the “Load Dataset” function to get X and y. Then, the data are pre-processed using the “Preprocess Data” function to obtain X_preprocessing data function to obtain X_preprocessed. The data were split into training and testing sets (X_train, X_test, y_train, y_test).

Step 4. Build the RNN Model

We begin by initializing a sequential model. Incorporate an RNN layer with 128 units; set return_sequences= true if required. Add a dropout layer with a dropout rate of 0.2 to prevent overfitting. This is followed by a dense output layer using a sigmoid activation function for binary classification tasks. Compile the model using the Adam optimizer, set the loss function to binary cross-entropy, and use accuracy as the evaluation metric.

Step 5. Train the RNN Model

The model is fitted using the training data (X_train, y_train) and is validated with the test set (X_test, y_test). Apply early stopping based on the validation loss to avoid overfitting. Assessment of the performance of the model on the test dataset.

Step 6. Main Function to Manage Workflow

Dedicated “Load” and “Preprocess” functions are used to import and prepare the dataset. The RNN was trained using the training data, and its performance was assessed on the test set. Present training metrics, such as loss and accuracy, along with the final test accuracy and loss values.

CNN for Anomaly Detection

Step 1. Load the Dataset

Import the dataset containing the image inputs (X) and their corresponding labels (y). Ensure that the data is in a suitable format, such as NumPy arrays or a pandas.DataFrame.

Step 2. Data Preprocessing

Scale the pixel values of X to fall within the [0, 1] range or standardize them by removing the mean. Reshape the data to fit the CNN input shape (samples, height, width, and channels).

Step 3. Load and Prepare Data

Invoke the “Load Dataset” function to retrieve X and y. The input data were normalized and reshaped to satisfy the requirements of CNN architecture.

Step 4. Construct the CNN Model

Initialize a sequential model and add convolutional layers with the chosen filter sizes and kernel dimensions. The output from the last convolutional layer is flattened, and dense layers are included for classification.

Step 5. Train the CNN Model

X_train and y_train are used to train the model, validating it with X_test and y_test. Integrating early stopping to monitor the validation performance. Evaluate the model's accuracy and loss of test data.

Step 6. Main Function for Execution Flow

Utilize the “Load” and “Preprocess” functions to handle dataset preparation. The CNN model was trained using the training set and evaluated on the test data, displaying the final performance metrics.

RESULT AND DISCUSSION

The health metrics visualization highlights key parameters such as heart rate, blood pressure, activity levels, sleep quality, and oxygen levels, providing a comprehensive overview of the health of the elderly. Stable indicators, including consistent oxygen saturation, sleep quality, and cardiovascular metrics, reflect normal functioning and overall well-being. By monitoring these metrics, caregivers can detect irregularities, such as abnormal vitals or low activity levels, signaling potential health risks. Real-time monitoring enables early detection and proactive care, thereby enhancing safety and quality of life. Intuitive graphs ensure that caregivers have quick access to critical insights for informed decision-making. The reliability of the system in capturing health trends reinforces its value in elderly health care monitoring.

Hyperparameter Settings

The models were designed to analyze datasets such as the UCI HAR, MIMIC-III, and WESAD, focusing on human activity classification, patient monitoring, and stress analysis (Table 2). For the UCI HAR dataset, a CNN with a learning rate of 0.001, Adam optimizer, batch size of 32, and 50 training epochs was used, featuring convolutional layers for feature extraction, and dense layers for classification. Sequential data from the MIMIC-III dataset were processed using a bidirectional model with similar hyperparameters optimized for temporal patterns. For MIMIC-III and WESAD, an LSTM model with a 0.01 learning rate, Adam optimizer, batch size of 32, and 50 epochs was employed, incorporating two LSTM layers with 30% dropout to prevent overfitting, and dense layers for predictions. These architectures effectively capture patterns in motion, sequential, and time-series data, ensuring an accurate and robust analysis across datasets.

Table 2. Hyperparameter settings of CNN, RNN, and LSTM.

Hyperparameter	CNN	RNN	LSTM
Number of layers	3–5 Convolutional layers	2–3 Recurrent layers	2–3 LSTM layers
Units per layers	32, 64, 128	64, 128	64, 128
Optimizer	Adam	Adam	Adam
Batch size	32	32	32
Learning rate	0.001	0.001	0.001
Epochs	50	50	50

Performance Metrics

The models were assessed using several key metrics: precision, recall, F1-score, accuracy, macro-average, and weighted average. These metrics help evaluate the performance of the models.

Accuracy

Accuracy reflects the overall performance of the model by showing the percentage of correct predictions, including both true positives and true negatives, across the entire dataset. Although it provides a broad assessment of model effectiveness, it can be deceptive when dealing with imbalanced data distributions.

$$\text{Accuracy } = \frac{\text{True Positive}}{\text{Total Sample}} \tag{1}$$

Precision

Precision evaluates the reliability of a model's positive predictions by determining the proportion of predicted positives that are actually correct. A high-precision score means that the model produces few false positives, making it especially valuable in situations where false positives have significant consequences.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{Flase Positive}} \tag{2}$$

Recall

Recall or sensitivity measures how well a model identifies actual positive cases. It focuses on detecting all relevant positive instances, making it important when missing a positive case is more critical than false positives.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{Flase Positive}} \tag{3}$$

F1-Score

F1-Score is the harmonic mean of precision and recall. It balances the tradeoff between precision and recall, ensuring that both metrics are considered. The F1-score is useful when dealing with imbalanced datasets, in which both false positives and false negatives matter.

$$\text{F1} - \text{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

Performance Evaluation

The CNN-LSTM model combines CNN for extracting spatial features from ECG or Photoplethysmography (PPG) signals and LSTM for analyzing temporal patterns, making it ideal for detecting heart anomalies, such as arrhythmia or tachycardia. This hybrid approach ensures high accuracy and reduces false positives, thereby enabling real-time monitoring in smartwatches (Figure 2). It continuously learns from new data, enhances predictions, and provides an early detection of cardiovascular issues. With CNN-LSTM, wearable devices offer reliable heart-health insights and emergency alerts (Table 3).

The WESAD dataset contains multimodal data, such as ECG, EDA, temperature, and motion signals for stress detection. It included stress, neutral, and amusement states of 15 participants. Metrics such as accuracy, precision, recall, F1-score, and ROC-AUC were used to evaluate model performance. CNNs extract features, RNNs analyze sequences, LSTMs capture temporal patterns, and DRL adapts effectively for stress classification (Table 4 and Figure 3).

The MIMIC-III dataset contains ICU patient records with time-series and categorical data from over 40,000 patients, supporting research on outcome prediction, disease diagnosis, and resource optimization. Performance metrics such as accuracy, precision, recall, F1-score, and PR-AUC were used to evaluate the effectiveness of the model. CNNs process structured data, RNNs capture long-term dependencies, and LSTMs handle irregular time-series data. DRL optimizes personalized treatment and resource allocation. MIMIC-III enables benchmarking and the development of models that integrate diverse inputs, thereby improving predictive accuracy and clinical insights (Table 5 and Figure 4).

Table 3. UCI HAR dataset performance metrics.

Model name	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
LSTM	80	78	76	77
CNN	82	81	79	80
RNN	78	76	74	75
DRL	76	74	72	73

Table 4. WESAD dataset performance metric.

	Model name accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
LSTM	76	82	74	71
CNN	81	76	72	70
RNN	64	76	82	69
DRL	73	74	75	87

Table 5. MIMIC III dataset performance metrics.

Model name	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
LSTM	72	70	68	69
CNN	74	73	70	71.5
RNN	70	68	65	66.5
DRL	68	66	64	65

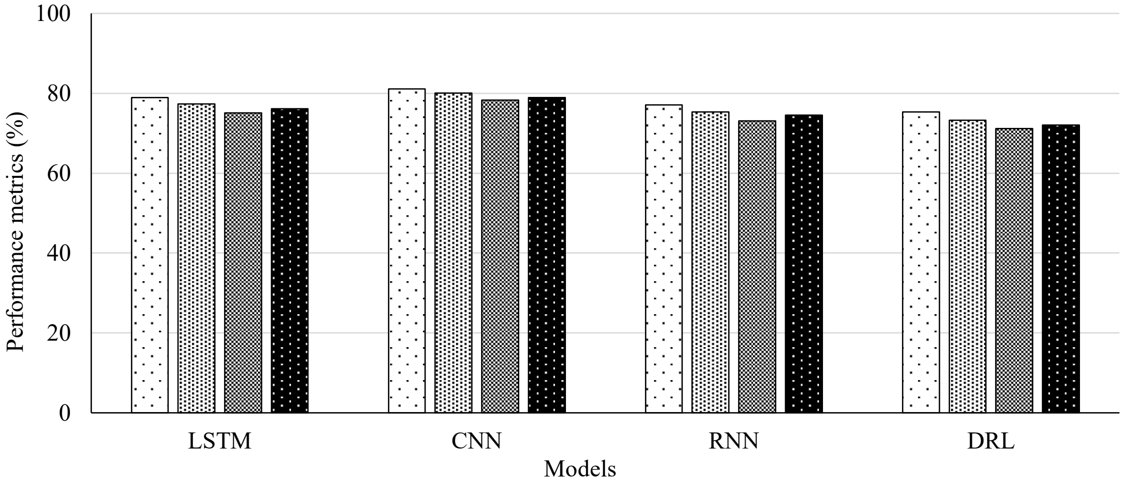

Figure 2. UCI HAR dataset performance metrics.

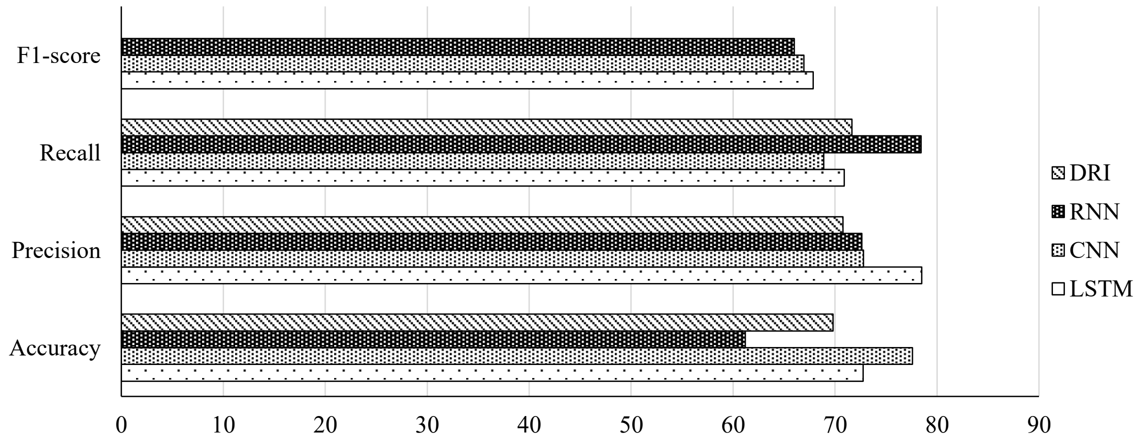

Figure 3. WESAD dataset performance metrics.

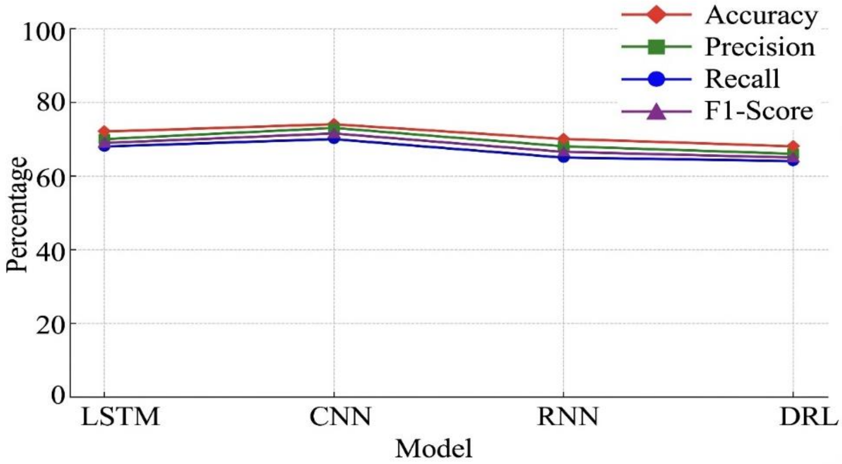

Figure 4. MIMIC III dataset performance metrics.

DISCUSSION

Visualization of health metrics plays a pivotal role in elderly healthcare by providing clear insights into key parameters such as heart rate, blood pressure, activity levels, sleep quality, and oxygen levels. By monitoring these indicators, caregivers can promptly detect abnormalities that may signal potential health risks and foster proactive care. Stable metrics, such as consistent oxygen saturation and sleep quality, reflect good overall health, whereas robust activity levels suggest positive physical engagement. Real-time monitoring of the system ensures the early detection of issues, empowering caregivers to make informed decisions. Visualization of stable metrics, including heart rate and blood pressure, offers reassurance to both caregivers and family members, confirming the effectiveness of the system in tracking health trends and providing timely alerts. This comprehensive approach enhances safety, quality of life, and the reliability of elderly healthcare monitoring.

CONCLUSION

The project highlighted that each algorithm used in the system was tailored for specific tasks in elderly health monitoring. LSTM models demonstrated strong performance in monitoring long-term health patterns, including tracking vital signs, such as heart rate, blood pressure, and glucose levels. Their strength lies in retaining and analyzing information over extended periods, making them well-suited for identifying subtle, progressive health changes, particularly for elderly individuals whose health may evolve gradually. On the other hand, deep reinforcement learning (DRL) is effective in making quick, real-time decisions in dynamic situations, such as responding to sudden changes in vital signs or detecting incidents like falls. By continuously learning from new data, DRL enables personalized health recommendations based on the evolving state of the patient. CNN is effective in analyzing sensor and image data, such as patterns from wearable devices, to recognize activities such as walking, sitting, or sleeping.

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