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Adaptive Hierarchical Deep Learning For Heterogeneous Iot Telemonitoring Networks

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Abstract
The rapid expansion of Internet of Things (IoT)-enabled telemonitoring systems has facilitated continuous healthcare monitoring through wearable sensors, smart medical devices, and remote patient monitoring platforms. However, conventional centralized learning approaches are constrained by privacy risks, communication overhead, scalability limitations, and performance degradation caused by Non-Independent and Identically Distributed (Non-IID) healthcare data across distributed devices. Existing federated and distributed learning frameworks often exhibit inefficient hierarchical coordination and limited adaptability in heterogeneous healthcare environments. To address these challenges, this research proposes a Hierarchical Deep Learning (HDL) model based on a Capuchin Search Algorithm-tuned Hierarchical Recurrent Neural Network (CSA-HRNN) for privacy-preserving telemonitoring applications. The model is evaluated using IoT-based telemonitoring healthcare datasets containing physiological signals, including heart rate, electrocardiogram (ECG), blood pressure, oxygen saturation, and body temperature measurements. Initially, the collected data are preprocessed using Min-Max normalization to eliminate scale variations and improve learning stability. Subsequently, Independent Component Analysis (ICA) is employed for feature extraction to obtain informative and statistically independent representations of physiological parameters. The proposed hierarchical architecture performs local model training on edge devices, followed by edge-level and cloud-level aggregation without sharing raw patient data. The model is implemented in Python. Experimental results demonstrate that the proposed CSA-HRNN model achieves an accuracy of 98.4%, precision of 0.983, recall of 0.982, and an F1-score of 0.981, while reducing communication overhead and accelerating convergence under Non-IID data environments. The findings confirm the effectiveness of the proposed model for reliable and intelligent IoT-based telemonitoring systems.

Keywords: Telemonitoring Systems, Wearable Sensors, Healthcare, Internet of Things (IoT), Privacy Preservation.

1. Introduction

Disease prediction and early diagnosis remain significant challenges in modern healthcare. To address these challenges, Remote Patient Monitoring (RPM), commonly known as telemonitoring systems, has emerged as an effective healthcare approach. Telemonitoring systems involve the use of communication and sensing technologies to monitor patients outside traditional hospital settings, enabling healthcare providers to assess patients' conditions remotely [1]. The effectiveness of telemonitoring depends not only on the technology employed but also on how well it is integrated into the healthcare environment and adapted to patient needs [2]. Through telemonitoring systems, healthcare professionals can continuously observe the progression of diseases and identify early signs of complications. This capability enables timely medical intervention, improves treatment outcomes, and reduces the likelihood of hospital admissions [3]. The integration of Internet of Things (IoT) technologies into telemonitoring systems for enhanced RPM healthcare enables instant data collection and transmission of physiological and health-related data. IoT-based telemonitoring solutions offer a promising method to improve healthcare accessibility, particularly for patients with health illnesses and those requiring long-term monitoring [4].Despite these advantages, the transmission of sensitive medical information raises important concerns regarding privacy and security. Therefore, telemonitoring systems must ensure end-to-end security, including secure data transmission within home networks, across the internet, and at healthcare endpoints, while maintaining proper management of patient information [5]. Various communication methods, such as phone calls, text messaging services, web-based platforms, and dedicated telemonitoring systems applications, are commonly used to support RPM healthcare. Recent advancements in wearable sensors, telemedicine, and healthcare sensors have transformed telemonitoring practices [6]. Wearable sensor devices enable continuous monitoring and analysis of patients' health conditions, supporting disease prevention, early diagnosis, and personalized treatment. Additionally, integrating camera systems with a telemonitoring system platform allows healthcare providers to perform visual assessments of patients, particularly in critical care environments. Modern telemonitoring technologies improve patient quality of life, enhance treatment adherence, reduce unnecessary hospital visits, and support more efficient healthcare delivery [7, 8].This research aims to train the CSA-HRNN model to extract hierarchical representations from IoT-based patient monitoring data, enabling accurate healthcare prediction. By leveraging edge–cloud collaboration, optimal feature selection, and hierarchical model aggregation, the model enhances patient data privacy, reduces communication overhead, and improves scalability.

Research Organization: This research is organized into five sections. Section 1 presents the introduction and background on telemonitoring systems for patients' healthcare. Section 2 reviews the existing research on patients' health monitoring. Section 3 describes the suggested approach in full. The findings of the experiment are discussed in Section 4. Section 5 takes up the research, highlighting contributions to reliable monitoring under telemonitoring of patient data.

2. Related Work

Development and validation of the highly valuable digital transformation for patient monitoring was investigated in [9] using the Minimal Viable Product (MVP) method for patient monitoring. The result shows a high level of patient satisfaction and patient adherence 7 ± 4.5 actions on average for each patient. However, only a small number of patients benefit from these health services. An intelligent telemonitoring system for solving patient problems in telemonitoring their own health was examined [10]. The Recovery Aid and Vital Signs Artificial Intelligence (VS-AI) Model are usedto monitor the patients; the result shows a patient accuracy rate of 81.22%. Problems in Overloaded phone lines, doctors' exposure to pathogens, and sick patients are examples of territorial health surveillance. lacking hospital access. Improvement of the cost-effectiveness and health monitoring of patients' heart rate to monitor the patient's daily activities was developed in [11], using the Microcontroller (PIC18F4550), and a Wi-Fi Module (ESP8266) incorporated for patient activity maintenance. The result obtained showed that 12.16% of the total energy consumed by the wearable sensors to monitor the patient's health is limited by the high energy utilized to charge the monitoring device. The Soft Transducer for Patient Vital Signal Monitoring was investigated in [12] using the Long Short-Term Memory Autoencoder (LSTM-AE). The performance of the experimental results showed an accuracy of over 93% for the detection of the patient, with a true positive rate exceeding 94%. It suffers from limited patient heterogeneity data. The integration of the latest innovative technology for the development of the healthcare therapy and monitoring system of the patient was done in [13]. The help of Human Activity Recognition (HAR) technology for the patient's privacy and activity protection is used for monitoring; therefore, the resulting level of healthcare accuracy is high. It suffers from the collected data being associated with each specific patient's identity. Technologies and functions of the telemonitoring application for the enhancement of healthcare services were explored [14]. The Recovery Aid method implementation for the monitoring of the patient's activities resulted in an extremely precise telemedicine system using a number of tools, such as a temperature and a saturation device, which is restricted to telemedicine only. However, validation of novel criteria is always a difficult task since it requires invasive methods like taking blood pressure samples.A proof-of-concept IoT-based RPM healthcare monitoring system to Monitor Patients' Health was carried out in [15]. The result revealed that with an enhanced interoperable remote health monitoring system using IoT and Fast Healthcare Interoperability Resources (FHIR), with scalability improvement, demonstrated the development of extendable IoT-based technologies for tackling major problems within an aging population. The application of AI-enabled IoT and Cloud Computing technology for monitoring the patient's health condition was investigated in [16],through the use of Transformer-based Self-Attention Model (TL-SAM). The result shows that the model is highly accurate on AI-enabled healthcare expenses, early disease detection, and timely intervention of patients, but it is prone to overfitting due to its complexity and small sample size. An innovative comprehensive health assessment technique with the application of the model for ensemble deep learning for IoT-based RPM was analyzed in [17]. An LSTM and Convolutional Neural Network (CNN) are applied to enhance the patient compliance rate, with the outcome being 97.5% accuracy in the monitoring of patients' physiological data; however, it suffers from limitations in terms of its generalization capability. To overcome these problems, the proposed CSA-HRNN combines cross-scale attention with a hybrid recurrent architecture for patient monitoring. To increase generalization, lessen overfitting, guarantee interpretability, and facilitate scalable, precise, and intelligent healthcare decision-making.

3. Methodology

An Adaptive HDL framework is proposed for patient health-data analysis in IoT-based telemonitoring environments. As shown in Figure 1, physiological parameters are collected through wearable sensors and RPM devices. The acquired data are normalized using the Min–Max Normalization technique, followed by feature extraction using ICA. The proposed CSA-HRNN model enables efficient communication, scalability, and accurate patient health prediction.

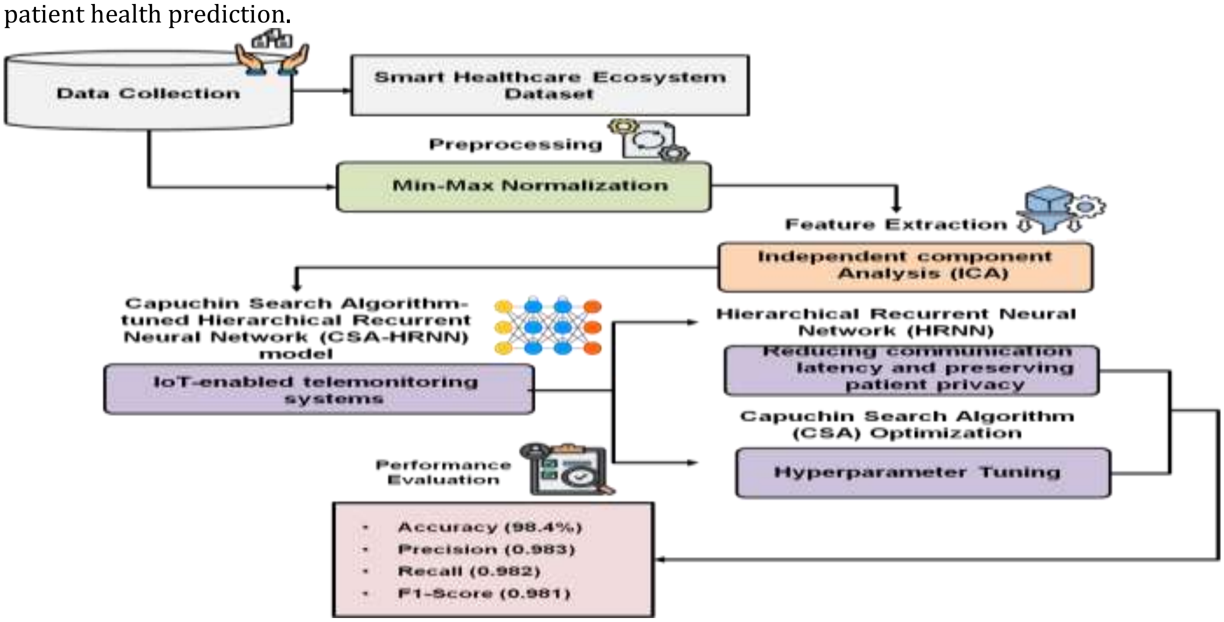


Figure 1: Methodology Workflow for IoT-based Patient Telemonitoring Systems

3.1 Data Collection

The dataset used for this research is the Smart Healthcare Ecosystem Dataset gathered from Kaggle (https://www.kaggle.com/datasets/zara2099/smart-healthcare-ecosystem-dataset). The dataset consists of 4000 observations in 18 columns of patients' health-related data, such as Heart Rate, Blood Pressure, Blood Oxygen Level, Body Temperature, Respiration Rate, Glucose Level, ECG Signal Intensity, Activity Level, and Sleep Duration Hours, which consist of various data like physiological parameters, information from wearable sensor devices, and electronic health parameters. The target column represents the patients' health status. The dataset is divided into 80% training data and 20% testing data to develop and evaluate the proposed HDL system based on the CSA-HRNN model for IoT-enabled telemonitoring applications.

3.2 Data Preprocessing using Min–Max Normalization for Feature Scaling

In this research, the initial physiological and IoT data gathered through wearable sensors and remotely operated monitoring equipment are first normalized through min-max normalization using the patient's data. This preprocessing technique plays an important role in ensuring the patient's optimal healthcare performance and feature scaling. Min-max normalization ensures that the smallest feature value is mapped to 0, the largest to 1, and the normalized feature scaling process is expressed in Equation (1).

$$\mathrm{W_{new}} = \frac{(\mathrm{W}-\mathrm{W_{min}})}{(\mathrm{W_{max}}-\mathrm{W_{min}})} \quad (1)$$

$\mathrm{W_{new}}$ represents the normalized patient output feature for improved training stability and enhanced predictive performance of the IoT telemonitoring model. W represents the raw features of patients' health data, $\mathrm{W_{max}}$and$\mathrm{W_{min}}$ represent the minimum and maximum values of the Heart Rate and Blood Pressure features in the smart healthcare dataset.

3.3 Feature extraction using Independent Component Analysis (ICA)

The ICA technique is used in this research as a reliable statistical signal processing method to separate hidden patients' features from diverse physiological signals gathered through IoT-based telemonitoring devices. The objective of ICA is to separate statistically independent components of observed signals, such as Blood Oxygen Level and Body Temperature, which are significant in capturing important physiological traits. This procedure is mathematically expressed in Equations (2 and 3).

$$\mathrm{w(s)} = \mathrm{Br(s)} \quad (2)$$

$$\mathrm{r(s)} = \mathrm{Gw(s)} \quad (3)$$

Where w(s) stands for the mixed IoT telemonitoring signals obtained through physiology-related and system-related characteristics such as Blood Oxygen Level, Body Temperature, and r(s) refers to the source components identified independently for better body temperature feature extraction, and B refers to the mixing matrix that remains the patient's unidentified data. In Equation (3), G stands for the estimated separation matrix obtained to extract independent physiological signals for the predictive performance of patient monitoring.

3.4 IoT Telemonitoring Networks with Hierarchical Deep Learning using Capuchin Search Algorithm-tuned Hierarchical Recurrent Neural Network (CSA-HRNN) for monitoring a patient's health data

The proposed HDL framework integrated with the CSA-HRNN enhances IoT-based telemedicine systems by providing accurate, scalable, and secure health monitoring. Physiological data collected from wearable sensors are processed locally at edge nodes, reducing communication overhead and latency. Hierarchical aggregation enables collaborative learning between edge and cloud layers, improving model efficiency. Furthermore, the CSA optimizes HRNN hyperparameters, resulting in higher prediction accuracy, faster convergence, and better generalization performance for heterogeneous and non-IID healthcare data environments.

Hierarchical Recurrent Neural Network (HRNN) for privacy-preserving and scalable patient monitoring: In the proposed HDL model, an HRNN is used for dependencies within the patient's physiological signal time series obtained from IoT telemonitoring devices. Every patient's node in the dataset, denoting a patient's data stream, is assigned to its corresponding patient, whereas the time series itself and also medical alerts with parameters. The probability of observing a time series is expressed using normally distributed errors, while each patient node parameter is connected to the corresponding parent through an informative hierarchical prior,as expressed in Equations (4 and 5).

$$q(\theta|Y,\tau) = \frac{q(Y|\theta,\tau)q(\theta)}{Q(Y)} \propto \prod_{m\epsilon J}\prod_{s=1}^{U_m} M(y_s^m; h(\theta_m, Y_{s-1}^m), \tau_m^{-1}) \prod_{m\epsilon J} M(\theta_m; \theta_{\pi_m}, \tau_{\theta_m}^{-1}J) \quad (4)$$

$$\theta^* = \underset{\theta}{argmax}\ log\, q(\theta|Y,\tau) \quad (5)$$

$q(\theta|Y,\tau)$ represents the Posterior distribution of HRNN parameters using the IoT telemonitoring patient data Y. $Q(Y)$ refers to the full multivariate patient data over time. y_s^m denotes the observed oxygen feature value at time s for the m^{th} patient/node. $q(\theta)$ represents the set of all patient model parameters of the HRNN, and θ_m denotes the set of GRU-based parameters for the m^{th} patient node. $\prod_{m\epsilon J}$ represents the parameter of the patient's sleep duration node with a proportionality factor $\propto$ that affects hierarchical learning, $\prod_{m\in J}^{U_m}$ denotes the precision factors that affect modeling accuracy due to noise. τ_m^{-1} refers to the Variance for the Gaussian error in node m. $h(.)$ represents the nonlinear function based on GRU for sequence patient monitoring with a medical alert. $M(.)$ refers to the probability distribution for Gaussian. U_m denotes the time steps involved in the sequence of a patient with fast communication$m$. J represents the identity matrix to maintain independence between patient parameter regularization. θ_{π_m} denotes the parent-child relation of patient glucose feature node m. In Equation (5), θ^* refers to the learned HRNN patient's parameters by Maximum A Posterior (MAP) estimation. $\underset{\theta}{argmax}\, log$ represents the use of the patient's parameters for maximum posterior probability.

Hyperparameter Tuning with Capuchin Search Algorithm (CSA) Optimization: The CSA method is adopted to find out the best values for the hyperparameter tuning of the suggested HRNN model to improve its patient predictive capability. CSA is a population-based metaheuristic algorithm based on the intelligent searching for patients by capuchin monkeys, with each capuchin representing a potential monitoring solution. The process of patient monitoring involves monitoring each patient with their physiological parameters. The updated rule for the patient velocity is mathematically expressed in Equation (6).

$$v_i^j(s+1) = \rho v_i^j(s) + b_1\left(y_{best_i}^j(s) - y_i^j(s)\right)q_1 + b_2\left(Best_i - y_i^j(s)\right)q_2 \tag{6}$$

$v_i^j(s+1)$ represents the velocity of patient respiration rate for the j^{th} capuchin solution in i dimension at iteration s. $\rho v_i^j(s)$ refers to the updated velocity of the patient's heart rate capuchin agent to be employed in future searches. $y_i^j(s)$ denotes the position of the j^{th} capuchin in the patient stress space of hyperparameter values. $y_{best_i}^j(s)$ represents the best solution found by the j^{th} capuchin agent during optimization. $Best_i$ denotes the best solution found by using the patient's ECG with all capuchin agents globally. $b_1 and b_2$ refer to the acceleration coefficients affecting the balance between patient monitoring exploration and patient monitoring exploitation, and $q_1 and q_2$ represent the random numbers from the range [0,1], the patient weight procedure expressed in Equation (7).

$$\rho = x_{max} - (x_{max} - x_{min})\left(\frac{s}{maxite}\right)^2 \tag{7}$$

ρ represents the inertia of the patient's weight, which regulates the effect of past patient velocities on search movement. $x_{max} and x_{min}$ refer to the upper and lower values for the inertia patients' healthcare data's weight regulating search adaptation. s denotes the number of current patient iterations in the optimization algorithm. $Maxite$ represents the maximum number of patient iterations that CSA is allowed to run. The patient's position movements are mathematically expressed in Equations (8, 9, and 10).

$$y_i^j(s+1) = Best_i + \frac{q_{cg}\left(v_i^j(s+1)\right)^2 sin(2\theta)}{h}, j < 2; 0.1 \le \delta \le 0.20 \tag{8}$$

$$y_i^j(s+1) = Best_i + \frac{q_{fg}q_{cg}\left(v_i^j(s+1)\right)^2 sin(2\theta)}{h}, j < \frac{m}{2}; 0.2 \le \delta \le 0.30 \tag{9}$$

$$y_i^j(s+1) = Best_i + q_{cg}\left(v_i^j(s+1) - v_i^j(s)\right), j < \frac{m}{2}; 0.75 < \delta \le 1.0 \tag{10}$$

$y_i^j(s+1)$ represents the patient position of the capuchin after optimization of HRNN hyperparameters. $Best_i$ denotes the best solution found by using the patient's ECG with all capuchin agents globally.q_{cg} refers to the patient probability factor for balance influencing patient movement stability.$v_i^j(s+1)$ represents the velocity of patient respiration rate for the j^{th} capuchin solution in i dimension at iteration s. θ represents the angular value influencing the nonlinear patient movement in CSA. h refers to the gravitational value influencing the movement dynamics during privacy position updating. δ denotes the control value influencing the conditions under which behavioral switching occurs, and faster convergence. j refers to the index denoting the capuchin agent being considered in the privacy of the patient's population.

In Equation (9), q_{fg} denotes the probability factor for patient elasticity improving patient exploration. s denotes the iteration of the condition $\frac{m}{2}$ for switching between phases of patient exploration. In Equation (10), $v_i^j(s)$ refers to the updated velocity of the patient heart rate capuchin agent to be employed in future search. Table 1 presents the hyperparameters of the proposed CSA-HRNN model for IoT-based Telemonitoring Systems for monitoring patients' condition.

Table 1: Hyperparameters of Proposed CSA-HRNN model for IoT-based Telemonitoring Systems

Hyperparameter	Value
Learning Rate	0.001
Hierarchical Layers	3

Hidden Neurons	256 / 128 / 64
Batch Size	64
Epochs	200
Dropout Rate	0.3
Optimizer	Adam
L2 Regularization	0.001
Sequence Length	50
Validation Split	0.2

4. Result

The proposed HDL model for IoT-based telemonitoring greatly boosts health prediction performance with the monitoring of patients' data. The proposed CSA-HRNN reaches high accuracy, precision, recall, and F1-score,and it outperforms traditional models with faster convergence, better scalability, and enhanced privacy protection. Table 2 depicts the experimental setup of the proposed CSA-HRNN model for IoT-based Patient Telemonitoring Systems.

Table 2: Experimental Setup for the Proposed CSA-HRNN Model for IoT Patient Monitoring

Category	Specification
Hardware Platform	Intel Core i9-13900K CPU, NVIDIA RTX 4090 GPU (24 GB), 64 GB DDR5 RAM, 2 TB NVMe SSD
Operating System	Windows 11 Pro (64-bit)
Development Environment	Python 3.11, Jupyter Notebook, VS Code
Deep Learning Model	TensorFlow 2.16, Keras
Data Processing & ML Libraries	NumPy 2.0, Pandas 2.2, SciPy 1.13, Scikit-learn 1.5
Visualization Tools	Matplotlib 3.9, Plotly 5.22
Hyperparameter Optimization	Capuchin Search Algorithm (CSA)
GPU Computing Platform	CUDA 12.4

Exploratory Data Analysis: Figure 2(a) illustrates the vital signs vary across different patient severity levels. It measures the density and range of physiological data to spot unusual patterns in unstable medical information, which helps to improve the patient's local decisions at edge nodes. Figure 2(b) shows the analysis maps of how key metabolic metrics' probabilities vary across diverse patient groups. It sets up shifting normal-range limits to help detect the odd patient health activity events. So, the system can generalize and predict health declines in patients monitored through multi-source IoT networks.

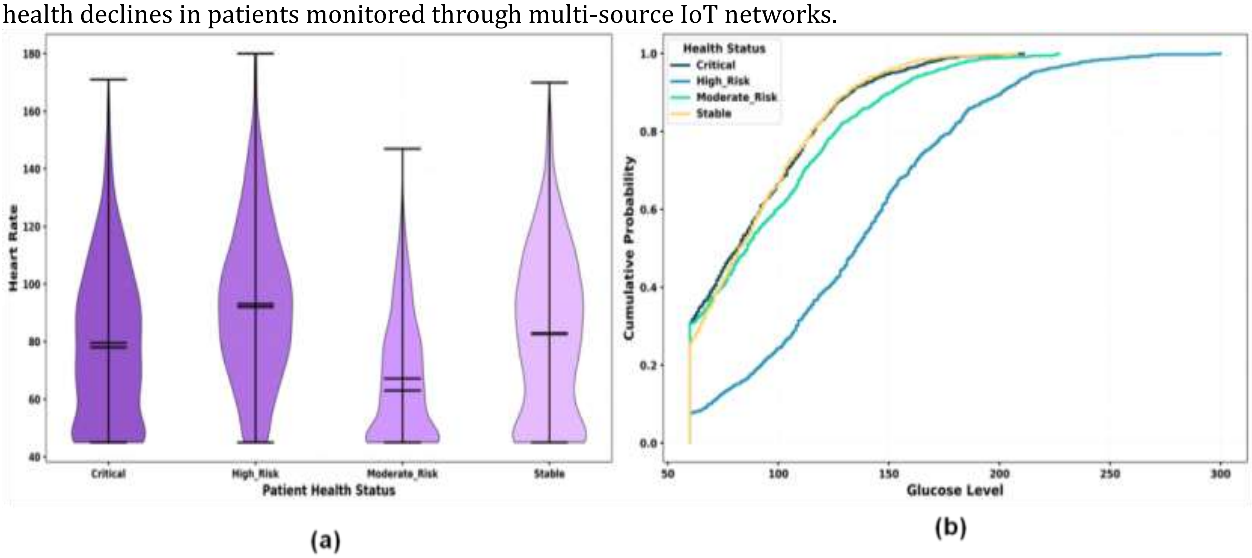


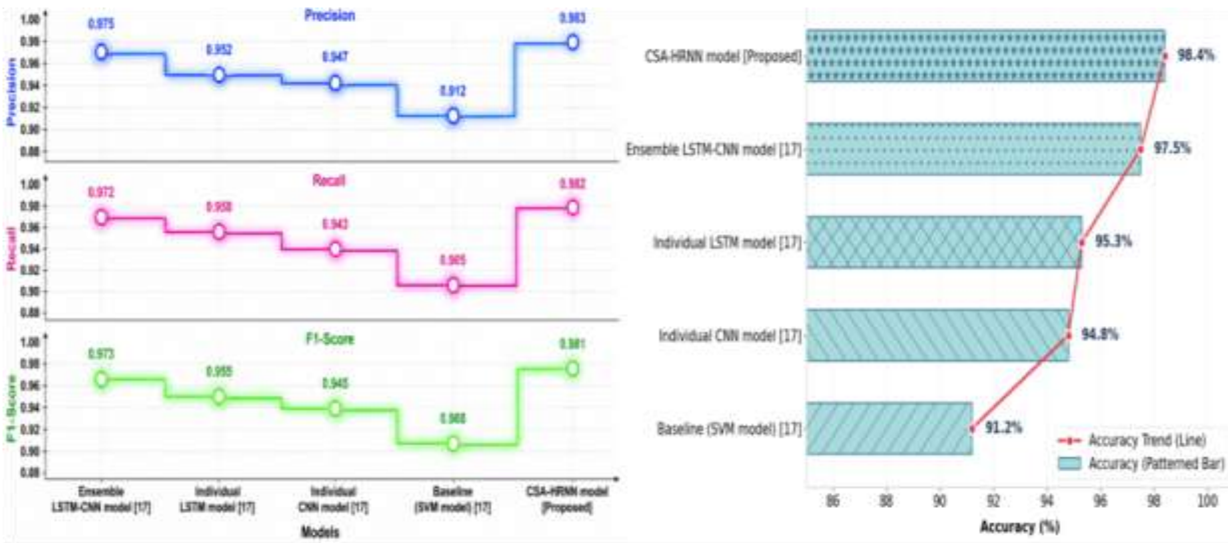
Figure 2: Data Analysis of (a) Distribution of Assessment Features across Patients' Health Risk Data and (b) Distribution of Patients' Biomarker Thresholds in HDL for Patients' Heterogeneous IoT Telemonitoring Networks

Performance Evaluation: The performance of proposed Adaptive HDL model was evaluated using IoT health monitoring by four metrics, such as accuracy, precision, recall, and F1-score. Accuracy measures the correct predictions about patient health. Precision measures the patient healthcare monitor and reduces false alarms. Recall measures effectively find actual health issues without missing any health-related information. An F1-score measures how well the system nicely balances precision of reducing patient false alarms and recall of actual health issues, making it a dependable option for keeping patients safe while protecting their privacy and managing large data loads.

Table 3 and Figure 3 (a and b) present the comparison evaluation of the existing and proposed methods for the security and privacy of a patient's Telemonitoring systems using IoT. The Ensemble LSTM-CNN model [17] shows high accuracy in patient healthcare. The Individual LSTM model [17] achieves a high accuracy in patient care monitoring. The Individual CNN model [17] highlights a high prediction of monitoring a patient. The Baseline (SVM model) [17] shows a low accuracy compared to all the previous existing methods. The proposed CSA-HRNN model achieves a better performance with a high F1-score of 0.981, recall of 0.982, accuracy of 98.4%, and precision of 0.983 compared to all other existing methods.

Table 3: Performance comparison of the proposed CSA-HRNN and traditional models for telemonitoring systems

Models	$Accuracy$ (%)	$Precision$	$Recall$	$F1-Score$
Ensemble LSTM-CNN model [17]	97.5	0.975	0.972	0.973
Individual LSTM model [17]	95.3	0.952	0.958	0.955
Individual CNN model [17]	94.8	0.947	0.943	0.945
Baseline (SVM model) [17]	91.2	0.912	0.905	0.908
CSA-HRNN model [Proposed]	98.4	0.983	0.982	0.981



(a) (b)

Figure 3: Performance Evaluation of the Proposed and the Existing Models (a) Precision, Recall, F1 score, and (b) Accuracy

Table 4 depicts the adaptive HDL model performs with the five-fold cross-validation for heterogeneous IoT telemonitoring networks. The CSA-HRNN model beats baseline models, with higher accuracy and lower variance. It proves the model with great generalization, stability, and robustness for handling diverse IoT health data across different care settings.

Table 4: Five-Fold Cross Validation for Non-IID healthcare data distributions in IoT Telemonitoring System

Model	**Fold**	**Accuracy (%)**	**Mean Accuracy (%)**	**Standard Deviation**	**95% Confidence Interval**
CSA-HRNN [Proposed]	1	98.1	98.38	0.17	98.38 ± 0.15

	2	98.3			
	3	98.6			
	4	98.4			
	5	98.5			

Discussion: This research focused on developing a novel Adaptive HDL architecture for Heterogeneous IoT telemonitoring network. The shortcomings of the current methods are Ensemble LSTM-CNN [17], Individual LSTM [17], Individual CNN [17], and SVM [17]. The Ensemble LSTM-CNN [17] model is very accurate, but it is limited by the multi-scale dense connections. On the other hand, the Individual LSTM [17] model suffers from the problem of limited generalization for patients from different backgrounds. The Individual CNN [17] model lacks the computational feasibility of the application of patient monitoring, while the Individual (SVM Model) [17] is very accurate but fails at RPM due to privacy concerns. The proposed CSA-HRNN model overcome these problems through its hierarchical aggregation ability at the edge-cloud; model training locally to ensure privacy, and an optimization scheme based on the CSA algorithm.

5. Conclusion

An Adaptive HDL model for IoT healthcare networks, focusing on boosting privacy and efficiency in analyzing patients' health data, consists of gathering body temperature, blood pressure, oxygen saturation, heart rate, and ECG data and cleaning it using Min-Max normalization. ICA helped extract key features from patients. The proposed CSA-HRNN model, which uses edge cloud aggregation, achieved 98.4% accuracy, with 0.983 precision, 0.982 recall, and 0.981 F1-score. Limitations are dataset diversity issues, extra computing costs at edge patient nodes, and sensitivity to network conditions. Future research needs to use data from multiple institutions and advanced AI that's easy to understand, along with adaptive aggregation methods. It makes models tougher, more interpretable, and capable of real-time health decisions. In the end, it'll help doctors make quicker and more precise choices in clinics.

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