Comprehensive Learning Salp Swarm Algorithm with Ensemble Deep Learning-based ECG Signal Classification on Internet of Things Environment

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Received: 11 August 2024 | Revised: 16 October 2024 | Accepted: 29 November 2024

 DOI: https://doi.org/10.48084/etasr.8702

ABSTRACT

The Internet of Things (IoT) in healthcare relates to implementing interconnected devices and systems for collecting and sharing healthcare information in real time. The integration of IoT in healthcare has the potential to enhance patient outcomes, reduce healthcare costs, and improve the efficacy of medical services. Electrocardiogram (ECG) is a non-invasive heart monitoring method that has become widely accessible due to user-friendly, low-cost, and lead-free wearable heart monitors. However, relying on overworked caregivers for manual monitoring is inefficient. This study develops a Comprehensive Learning Salp Swarm Algorithm with Ensemble Deep Learning (CLSSA-EDL) technique for ECG signal classification in IoT healthcare. The objective of CLSSA-EDL is to detect and classify ECG signals to support decision-making in the IoT healthcare environment. The CLSSA-EDL approach employs the DenseNet201 feature extraction method, with hyperparameters optimally selected by the CLSSA system. For ECG signal detection and classification, an ensemble model using a Stacked Autoencoder (SAE), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM) is utilized. The CLSSA-EDL technique was evaluated on a benchmark ECG dataset, achieving an accuracy of 98.7%, sensitivity of 97.5%, and specificity of 99.1%, demonstrating superior performance compared to recent algorithms.

Keywords-Internet of Things; deep learning; ECG signals; healthcare; ensemble models; parameter tuning

I. INTRODUCTION

Researchers investigate ways to reduce human effort using Artificial Intelligence (AI) and the Internet of Things (IoT). IoT is based on sensors, communication technologies, and data processing techniques [1]. A hidden pattern is recognized in the input data, and its class is assigned using classification techniques. This technology might benefit many fields, including agriculture, meteorology, industry, and medicine [2, 3]. To better serve patients, the healthcare industry is exploring concepts such as Medical Cyber-Physical Systems (MCPS) that combine digital components, such as networks and software, with physical ones, such as sensors and human signals. Sensors receive readings from the body and send them across a network to be analyzed. The software then takes action, such as sending a warning, diagnosing, or even treating the patient to improve his health. Due to the high cost of in-hospital care, telemedicine, home care, sports activity monitoring, and assisted living have gained great interest [4]. Home and mobile monitoring of physical activities and vital signs allows health to be evaluated remotely at any time [5]. The human body has a complicated electromechanical mechanism that enables smart healthcare devices to monitor different kinds of biomedical signals. The classification of Electrocardiogram (ECG) heartbeats is a considerable part of smart healthcare services, as it can indicate the presence of many cardiovascular problems. Diseases cause defects in the ECG signal [6]. Initial identification through an ECG allows for choosing appropriate cardiac medication and is extremely significant and useful in reducing strokes.

Critical features are derived from ECG signals to recognize heart disease [7]. However, noise is introduced into the ECG signal during the data transmission and collection process, which has a detrimental effect on diagnosis accuracy. Data capitalization is a critical function of the IoT cloud. The IoT cloud typically provides a data analysis platform to extract the appropriate data from ECG signals. Feature Selection (FS), classification, and extraction are the main stages in classifying the ECG heartbeat structure. Preprocessing raw ECG signals is crucial to reducing different noises. Feature extraction is the primary step, where the ECG is processed to acquire attributes for detecting arrhythmia. FS aims to select appropriate feature subsets of ECG data to achieve superior classification performance and provide substantial influence in heart disease diagnosis [8]. To solve this issue, a subsystem translates the pattern into features that become condensed representations of patterns with only significant data [9]. Today, research uses optimized FS methods to reduce or optimize attributes and eliminate redundant, unrelated, or noisy features.

Integrating IoT into healthcare systems has significantly improved patient monitoring and healthcare delivery. Among various healthcare applications, continuous monitoring of cardiac health using ECG signals has gained prominence due to the increasing prevalence of cardiovascular diseases. Traditional ECG monitoring systems rely heavily on manual analysis by healthcare professionals, which can be time-consuming and prone to human error. This study proposes a novel Comprehensive Learning Salp Swarm Algorithm with Ensemble Deep Learning (CLSSA-EDL) for ECG signal classification in a healthcare IoT environment to address these challenges. The key contributions of the proposed method include:

- High accuracy: CLSSA-EDL leverages advanced deep learning models, such as DenseNet201, for feature extraction and an ensemble of Stacked Autoencoder (SAE), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM) for classification, resulting in superior accuracy.
- Optimized hyperparameters: CLSSA ensures optimal selection of hyperparameters, enhancing the performance and generalizability of the model.
- Robustness: The proposed method demonstrates high sensitivity and specificity, making it reliable for real-time detection and classification of ECG signals.
- Efficiency: Integration of IoT technology facilitates real-time data collection and processing, reducing the burden on healthcare professionals and improving patient outcomes.

This study presents the CLSSA-EDL technique for ECG signal classification in IoT. The objective of this system is mainly to detect and classify ECG signals for decision-making in the IoT healthcare environment. To accomplish this, the proposed system employs the DenseNet201 feature extraction approach and optimally chooses its hyperparameters. For ECG signal detection and classification, an ensemble model is used, utilizing three DL systems: GRU, LSTM, and SAE. The CLSSA-EDL technique was tested using a benchmark ECG dataset, and the results of several measures were examined.

In [10], the optimal ECG features were investigated to implement a personal authentication mechanism using reinforcement learning. In [11], another user authentication mechanism was proposed, based on ECG signals and utilizing DL methods. In [12], current ML and Metaheuristic Optimization (MHO) were used to detect arrhythmia. In [13], a modular 1D-CNN model was proposed for ECG arrhythmia analysis in fog-cloud environments. In [14], a novel method was introduced for detecting SVCA utilizing ECG signals, and the Fixed Frequency Range Empirical Wavelet Transform (FFREWT) filter was introduced for multiscale analysis of ECG signals. In [15], a new detection technique was presented, using raw ECG signals from wearable telehealth mechanisms. In [16], an ensemble-oriented classification method combined the efficiency of CNNs with bio-inspired and linear methods, such as KNN, RF, and SVM. The studies in [17-21] highlight a strong emphasis on using advanced computational techniques for classification tasks across diverse domains.

Continuous monitoring of cardiac health using ECG signals is crucial due to the increasing prevalence of cardiovascular diseases. Various conventional techniques have been developed for ECG signal classification, but each has limitations. For example, SVMs are sensitive to parameter selection and can be computationally intensive, KNN suffers from the curse of dimensionality, leading to decreased performance as the number of features increases, Artificial Neural Networks (ANNs) are prone to overfitting and can be difficult to interpret, making them less suitable for real-time applications, and Convolutional Neural Networks (CNNs) require substantial computational resources and are challenging to deploy in resource-constrained IoT environments. This study attempts to address these limitations. The proposed approach combines the strengths of various deep learning models and an optimization algorithm to achieve high accuracy, robustness, and efficiency. Specifically, the proposed method:

- Utilizes DenseNet201 for effective feature extraction, leveraging its ability to capture intricate patterns in ECG signals.
- Employs an ensemble model comprising SAE, GRU, and LSTM to enhance classification performance by capturing spatial and temporal features.
- Optimizes hyperparameters using CLSSA, ensuring optimal model configuration and improving generalizability.
- Demonstrates superior performance with an accuracy of 98.7%, sensitivity of 97.5%, and specificity of 99.1%, outperforming recent state-of-the-art methods.

II. THE PROPOSED MODEL

The objective of CLSSA-EDL is to detect and classify ECG signals for decision-making in the IoT healthcare environment. The CLSSA-EDL system encompasses DenseNet201 feature extraction, CLSSA-based hyperparameter tuning, and ensemble learning-based classification to accomplish this.

A. Data Preprocessing

Six image processing parameters were considered to prevent data loss and distortion: center crop, hue, gamma, saturation, and contrast [22].

B. Feature Extraction

The DenseNet-201 architecture was applied in this study to develop a collection of feature vectors. In TL, a pre-training method, previously trained on a larger database for a particular task can be exploited for other downstream tasks [23]. The DenseNet201 architecture is trained on the ImageNet dataset and consists of three transition layers, four dense blocks, max-pooling, and convolution layers. It increases the data flow amongst the layers and allows the method to remove and capture the features efficiently, defined as follows:

$$f_l = H_l([f_0{}' f_1, \dots, f|_{-1}]) \tag{1}$$

where l shows the layer, and $[f_0, f_{1,\dots,}/f_{l-1}]$ denotes the feature concatenation. H_l denotes a composite function, which includes a 3×3 convolutional operation, BN, and ReLU activation. A dense block was included in the architecture to adjust the size of feature maps. The transition layer performs an 1×1 convolutional layer followed by 2×2 avg-pooling. The small growth rate has defined the effect of all the layers to include new data to the network's incorporated knowledge.

C. CLSSA-based Hyperparameter Tuning

CLSSA was used to fine-tune the hyperparameters of DenseNet-201. A swarm optimizer approach, introduced by SSA, encourages salps to cluster together in water [24]. As a starting point, the method introduces a salp population. The n-salp swarm x is described as a 2D matrix.

$$X_i = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_d^1 \\ x_1^2 & \ddots & \ddots & x_d^2 \\ \vdots & \ddots & \ddots & \vdots \\ x_1^n & x_2^1 & \dots & x_d^n \end{bmatrix} \tag{2}$$

$$x_i^1 = \begin{cases} F_i + c_1((ub_i - lb_i)c_2 + lb_i)\ c_3 \geq 0.5 \\ F_i - c_1((ub_i - lb_i)c_2 + lb_i)\ c_3 < 0.5 \end{cases} \tag{3}$$

where F_j shows the food location in the j^{th} dimension, x_i^1 represents the location of chain salps leader in the j^{th} dimension, c_2 and c_3 are two random numbers, and lb_j and ub_j denote the lower and upper limitations of the salps position. From this iteration procedure, the key control parameter is c_1, stabilizing the exploitation and exploration stages, expressed as follows:

$$c_1 = 2e^{-\left(\frac{4t}{T\max}\right)^2} \tag{4}$$

where $Tmax$ represents the maximal number of rounds, and t denotes the existing iteration. The followers' position can be updated using:

$$x_i^j = \frac{1}{2}k * time^2 + s_0 time \tag{5}$$

for $i \geq 2$, where x_i^j denotes the location of the j^{th} salp in the i^{th} dimension. s_0 denotes an initial speed with:

$$k = \frac{s_{final}}{s_0} \tag{6}$$

where $s_{final} = \frac{x - x_0}{time}$, and $time$ denotes the time. In this work, the iteration counts denote the amount of time required.

At first, in every cycle, the particle population can be divided arbitrarily into two groups of equivalent size. Next, competition is introduced among the particles from all the groups. The particle with the maximum fitness value can be declared a winner, and then it can be suddenly developed for subsequent iterations. After learning the winner, the loser modifies the velocity and location. The mathematical expression of the location and velocity of the loser is given as:

$$V_l^{t+1} = R_1^t V_l^t + R_2^t (X_w^t - X_l^t) + \phi R_3^t (X^{-t} - X_l^t) \tag{7}$$

$$X_l^{t+1} = X_l^t + V_l^{t+1} \tag{8}$$

where t denotes the existing iteration, R_1^t, R_2^t, R_3^t show the randomly created vector within $[0,1]^n$, and X_w^t and X_l^t specify the winner and loser particles, respectively. X^{-t} represents the mean location of the existing swarm at t iteration, and ϕ represents the control parameter of X^{-t}.

The winner can be updated based on the SSA, which ensures a high-quality novel searching agent and a simple update of the winner. Hence, the competition mechanism comprises CL-SSA, which separates the solution as a loser and a winner. Next, the competition-based learning strategy updates the loser particle, allowing the loser to explore the search space. Finally, SSA updates the winning particle to upgrade and enhance all the winning particles. CL-SSA is initiated by a first population of N individuals. The upper and lower boundaries can limit an individual's search space by:

$$X_i^j = lb_i + rand \times (ub_i - lb) \quad (9)$$

where i shows the amount of arbitrary candidate solutions $i \in \{1,2,\dots,n\}$ from the searching spaces, j indicates the problem size $j \in \{1,2,\dots,d\}$, and X_i^j denotes the initial search agent. The upper and lower limitations are represented as ub_i and lb_i, respectively. In the CL-SSA technique, a pairwise competition process can segregate the solution into different classes of losers and winners. A better fitness level characterizes the winner, whereas the defeated party shows a lesser fitness level.

$$V_l^{t+1} = R_1^t V_l^t + R_2^t(X_w^t - X_l^t) + \phi R_3^t(X^{-t} - X_l^t) \quad (10)$$

$$X_l^{t+1} = X_l^t + V_l^{t+1} \quad (11)$$

where t represents the existing iteration, R_1^t, R_2^t, and R_3^t are random vectors within $[0,1]^n$, X_w^t and X_l^t represent the winner and loser particles, correspondingly, ϕ denotes the control parameter of X^{-t} influence, and X^{-t} specifies the mean location of the existing swarm at the t iteration. Furthermore, implicit multiplication represents Hadamard's component-wise vector multiplication operation. Then, the loser individual is updated, and the SSA upgrades the winner individually.

$$x_w^{t+1} = \begin{cases} Xbest + c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 \geq 0.5 \\ Xbest - c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 < 0.5 \end{cases} \quad (12)$$

where x_w^{t+1} signifies the winner's location in the j^{th} dimension, lb_j and ub_j show the lower and upper boundaries, respectively, $Xbest$ shows the better location, and c_2 and c_3 indicate two random numbers within $[0,1]$. The key control parameter is c_1, stabilizing the exploration and exploitation stages.

The decreased classification error rate can be an FF, as represented in:

$$fitness(x_i) = ClassifierErrorRate(x_i) = \\ = \frac{No.\ of\ misclassified\ instances}{Total\ No.\ of\ instances} * 100 \quad (13)$$

D. Ensemble Classification Model

In this work, ensemble DL models, such as GRU, LSTM, and SAE, perform the ECG signal classification process. Using distinct methods, majority voting can be assumed to be easier and more productive when integrating the forecasts achieved. Every class vote can be counted on the input classification, and the majority class can be chosen [25].

Assume a trained set and group of classifiers as $h_1, h_2, \dots, h_n$, and each classifier is trained on a training set. Thus, the classifier makes predictions. The classifier h_1 creates the prediction y_1, classifier h_2 prediction y_2, and classifier h_n prediction y_n. Next, voting is used to reach the last prediction. Voting decreases n-classes forecasts to a single data point as a single class. This process can be applied to get the last vote, expressed in:

$$y_f = mode\{h_1(x), h_2(x), \dots, h_n(x)\} \quad (14)$$

Considering $h_i(x) = y_i(x)$, applying majority voting is the same as asking a collection of experts to vote for a certain decision. In this method, the possibility of making any prediction errors can be negligible.

1) GRU

GRU is a simplified and optimized version of LSTM. The GRU approach improves the input and forget gates in the LSTM model by single update gates [26]. The GRU model has numerous benefits over LSTM, involving improved forecasting performance, reduced training parameters, and fast learning time.

$$r_t = \sigma(x_t W_{xr} + H_{t-1} W_{hr} + b_r) \quad (15)$$

$$Z_t = \sigma(x_t W_{xz} + H_{t-1} W_{hz} + b_z) \quad (16)$$

$$\widetilde{H}_t = \tanh(x_t W_{hx} + R_t \odot H_{t-1} W_{hh} + b_h) \quad (17)$$

$$H_t = (1 - Z_t) \odot H_{t-1} + Z_t \odot \widetilde{H}_t \quad (18)$$

where $\odot$ represents the component-wise multiplication, σ denotes a sigmoid activation function with the output ranging within [0, 1], H_{t-1} is previous data, R_t indicates the reset gate, Z_t denotes the update gate, and $\widetilde{H}_t$ denotes a candidate's hidden state.

2) LSTM

LSTM is a variant of RNNs, which can be integrated with the concepts of gates and memory cells to store and control the data flow [27]. The input data flow passes among h_{t-1} and x_t, and by managing the forget, input, and output gates of the memory unit, and c_{t-1} and h_{t-1} are upgraded to c_t and h_t, obtaining the neuron output. The calculations are given as:

$$f_t = sigmoid\left(\theta_f \cdot [h_{t-1'} x_t] + b_f\right) \quad (19)$$

$$i_t = sigmoid(\cdot [h_{t-1'} x_t] + b_i) \quad (20)$$

$$0_t = sigmoid(\theta_0 \cdot [h_{t-1'} x_t] + b_0) \quad (21)$$

$$\tilde{c}_t = \tanh(\theta_c \cdot [h_{t-1'} x_t] + b_c) \quad (22)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot c_t \quad (23)$$

$$h_t = 0_t \odot \tanh(c_t) \quad (24)$$

where tanh and σ define the tangent and sigmoid activation functions, correspondingly. The outcome range of tanh is within $[-1,1]$ to normalize the output. The outcome level of sigmoid among 0 and 1 is applied to simulate the gate opening. $h_t \in (-1,1)^h$ indicates the Hidden Layer (HL) vector. $x_t \in \mathbb{R}^d$ denotes the input vector of the LSTM model, $i_t \in (0,1)^h$ represents the input or upgrade gate activation vector, $f_t \in (0,1)^h$ is the activation vector of the forget gate, $0_t \in (0,1)^h$ represent the activation vector of the output gate, $\widetilde{c_t} \in (-1,1)^h$ represents the input activation vector of cells, and $c_t \in \mathbb{R}^h$ signifies the cell state vector.

3) SAE Model

SAE is an autoencoder configuration that increases the sparsity boundary for the loss function. Simultaneously, some HL nodes are active, so the whole autoencoder network is designed sparsely [28]. Let us use the sigmoid HL activation function. The HL output uses one to represent an active node and zero for an inactive node. According to this, the K_L dispersion is established to measure the similarity among the average activation result of a specific HL node and sparsity ρ as:

$$K_L(\rho||\hat{\rho}_j) = \rho \log \frac{\rho}{\hat{\rho}_j} + (1-\rho)\log \frac{1-\rho}{1-\hat{\rho}_j} \quad (25)$$

$$\hat{\rho}_j = \frac{1}{m}\sum_{i=1}^{m} a_j\,(x_i) \quad (26)$$

where $\hat{\rho}_j$ signifies the average sparse activation, x_j refers to the trained samples, and m denotes the count of trained samples. $a_j(x)$ stands for the response output of the j^{th} node of the HL to the i^{th} sample.

Usually, the sparsity coefficient ρ is fixed to 0.1. The higher the KL divergence, the larger the variance among ρ and $\hat{\rho}_j$, and a KL divergence equal to 0 means that the two have been entirely equivalent. The KL dispersion is the additional consistent term to use in the autoencoder function for constraining the sparse rows of the whole autoencoder:

$$JSAE\,(W,b) = J_{AE}(W,b) + \beta \sum_{j=1}^{m} K_L\,(\rho||\hat{\rho}_j) \quad (27)$$

where β implies the weighted coefficient of sparse constraints.

III. RESULTS AND DISCUSSION

This section examines the results of the CLSSA-EDL method on the MIT–BIH Arrhythmia Database [29-34]. The dataset comprises 6000 instances with three classes, as shown in Table I.

TABLE I. DATASET DETAILS

Classes	No. of Instances
Left Bunch Bundle Block (LBBB)	2000
Normal (N)	2000
Right Bunch Bundle Block (RBBB)	2000
Total Number of Instances	**6000**

Figure 1 shows the confusion matrices of the CLSSA-EDL system at 80:20 TRP/TSP on ECG signal classification. Table II and Figure 2 show the ECG signal classification analysis using the CLSSA-EDL method at 80:20 TRP/TSP. The CLSSA-EDL system effectively classified ECG signals under the three class labels. For 80 % of TRP, the CLSSA-EDL system achieved average $accu_y$ of 98.76%, $prec_n$ of 98.17%, $sens_y$ of 98.14%, $spec_y$ of 99.07%, and F_{score} of 98.15%. For 20% of TSP, the CLSSA-EDL system achieved average $accu_y$ of 99.33%, $prec_n$ of 98.99%, $sens_y$ of 99%, $spec_y$ of 99.50%, and F_{score} of 98.99%. Figure 3 illustrates the $accu_y$ of the CLSSA-EDL system in training and testing, indicating that the CLSSA-EDL technique obtains higher $accu_y$ as epochs increase. The maximal validation $accu_y$ shows that CLSSA-EDL attained proficiency with 80:20 of TRP/TSP.

TABLE II. ECG SIGNAL CLASSIFIER OUTCOME OF CLSSA-EDL SYSTEM ON 80:20 OF TRP/TSP

Class	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{Score}
Training Phase (80%)					
Left Bunch Bundle Block (LBBB)	98.96	98.19	98.68	99.09	98.44
Normal (Normal)	98.90	99.42	97.23	99.72	98.31
Right Bunch Bundle Block (RBBB)	98.44	96.89	98.51	98.40	97.70
Average	98.76	98.17	98.14	99.07	98.15
Testing Phase (20%)					
Left Bunch Bundle Block (LBBB)	99.75	99.26	100.00	99.62	99.63
Normal (Normal)	99.17	99.50	98.05	99.75	98.77
Right Bunch Bundle Block (RBBB)	99.08	98.20	98.96	99.14	98.58
Average	99.33	98.99	99.00	99.50	98.99

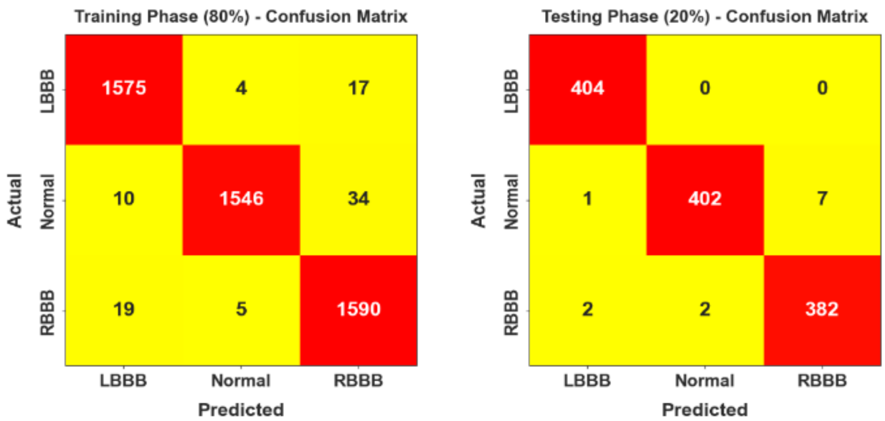

Fig. 1. Confusion matrices of CLSSA-EDL system (a) 80% of TRP and (b) 20% of TSP.

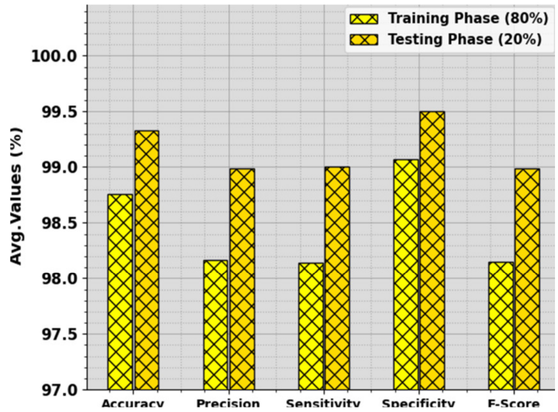

Fig. 2. Average results of CLSSA-EDL with 80:20 TRP/TSP.

Fig. 3. Accuracy of CLSSA-EDL algorithm under 80:20 of TRP/TSP.

Table III and Figure 4 show the ECG signal classification results of the CLSSA-EDL approach at 70:30 TRP/TSP. The results show that CLSSA-EDL obtained effectual classification of ECG signals under 3 class labels. Based on 70% of TRP, the CLSSA-EDL method attained average $accu_y$ of 97.43%, $prec_n$ of 96.17%, $sens_y$ of 96.13%, $spec_y$ of 98.07%, and F_{score} of 96.14%. On 30% of TSP, the CLSSA-EDL system attained average $accu_y$ of 98.04%, $prec_n$ of 97.05%, $sens_y$ of 97.07%, $spec_y$ of 98.53%, and F_{score} of 97.05%.

TABLE III. ECG SIGNAL CLASSIFIER OUTCOME OF CLSSA-EDL SYSTEM ON 70:30 OF TRP/TSP

Class	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{Score}
Training Phase (70%)					
Left Bunch Bundle Block (LBBB)	97.40	95.03	97.49	97.36	96.25
Normal (N)	97.48	97.35	94.97	98.72	96.15
Right Bunch Bundle Block (RBBB)	97.40	96.14	95.93	98.12	96.03
Average	97.43	96.17	96.13	98.07	96.14
Testing Phase (30%)					
Left Bunch Bundle Block (LBBB)	98.00	96.01	97.71	98.13	96.85
Normal (N)	98.17	98.32	96.22	99.16	97.26
Right Bunch Bundle Block (RBBB)	97.94	96.82	97.28	98.30	97.05
Average	98.04	97.05	97.07	98.53	97.05

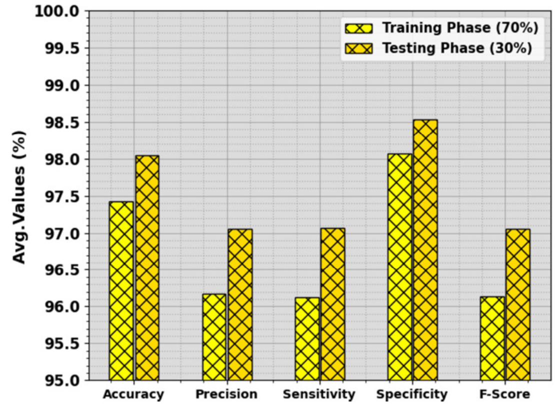

Fig. 4. Average results of CLSSA-EDL with 70:30TRP/TSP.

Figure 5 shows the $accu_y$ of CLSSA-EDL through the training and validation with 70:30 TRP/TSP, indicating that it achieved higher accuracy values over increasing epochs. Moreover, the increased validation $accu_y$ over the training $accu_y$ shows that CLSSA-EDL is efficient at 70:30 TRP/TSP. Figure 6 shows the loss investigation of the CLSSA-EDL method during training and validation with 70:30 TRP/TSP. These results show that the CLSSA-EDL approach reaches closer training and validation loss values. Thus, the CLSSA-EDL method learns efficiently with 70:30 of TRP/TSP.

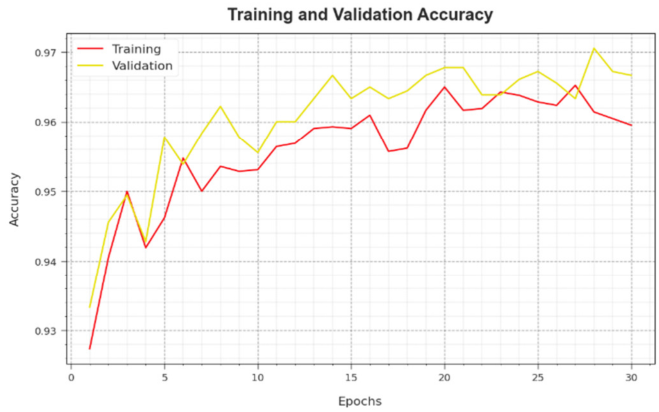

Fig. 5. $Accu_y$ curve of CLSSA-EDL with 70:30 TRP/TSP.

Fig. 6. Loss curve of CLSSA-EDL with 70:30 of TRP/TSP

Table IV and Figure 7 show an overall comparison of the CLSSA-EDL with existing techniques [35]. The results show that SVM, ANN, and CNN models obtained lower performance with the lowest classification results, while the LSTM-CNN and modified U-Net models had better classification performance. The ResNet model achieved better results with $accu_y$ of 99.06%, $sens_y$ of 93.21%, $spec_y$ of 98.97%, and F_{score} of 95.81%. However, the CLSSA-EDL method attained better performance with higher $accu_y$ of 99.33%, $sens_y$ of 99%, $spec_y$ of 99.50%, and F_{score} of 98.99%. Therefore, the CLSSA-EDL technique can be employed to produce an accurate classification process.

TABLE IV. COMPARISON ANALYSIS OF CLSSA-EDL WITH OTHER APPROACHES

Methods	$Accu_y$	$Sens_y$	$Spec_y$	F_{score}
SVM	87.45	90.95	96.70	82.19
ANN	89.49	92.82	97.18	84.98
CNN	91.92	94.40	97.95	88.93
LSTM-CNN	98.10	97.50	98.95	89.30
ResNet	99.06	93.21	98.97	95.81
Modified U-Net	97.32	94.44	98.78	89.96
CLSSA-EDL	**99.33**	**99.00**	**99.50**	**98.99**

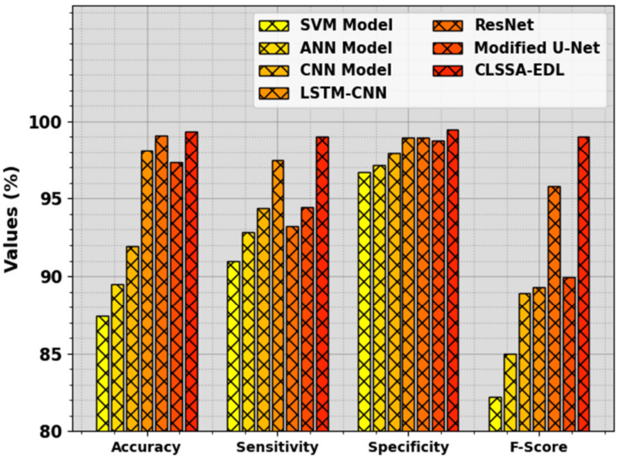

Fig. 7. Comparison of CLSSA-EDL model with other approaches.

IV. DISCUSSION

Table IV compares the proposed CLSSA-EDL technique with existing methods, including SVM, ANN, CNN, LSTM-CNN, ResNet, and Modified U-Net. The comparison is based on four key performance metrics: accuracy, sensitivity, specificity, and F-score. An expanded analysis and discussion of the results follow, comparing the proposed with existing models.

A. SVM

The SVM model achieved 87.45% $accu_y$, 90.95% $sens_y$, 96.70% $spec_y$, and 82.19% F_{score}. SVMs are powerful linear classifiers that can handle non-linear data using kernel functions. However, their performance is limited by the choice of kernel and parameters, often insufficient to capture complex patterns in ECG signals. SVMs cannot handle high-dimensional and highly non-linear data effectively. They also require extensive parameter tuning and are not robust to noise. The proposed CLSSA-EDL model overcomes these limitations using an ensemble of deep learning models that can capture linear and non-linear relationships more effectively.

B. ANN Model

The ANN model achieved 89.49% $accu_y$, 92.82% $sens_y$, 97.18% $spec_y$, and 84.98% F_{score}. ANNs, with their ability to learn non-linear representations, perform better than SVMs. However, their shallow architecture limits their capacity to learn complex hierarchical features. ANNs are prone to overfitting, especially with small datasets, and require careful regularization and tuning. The CLSSA-EDL method, with its comprehensive learning strategy, enhances generalization and mitigates overfitting by leveraging multiple models and optimized hyperparameters.

C. CNN

The CNN model achieved 91.92% $accu_y$, 94.40% $sens_y$, 97.95% $spec_y$, and 88.93% F_{score}. CNNs excel at extracting spatial features from data, making them well-suited for image and signal classification tasks. Their ability to capture local dependencies in ECG signals contributes to their improved performance. However, CNNs may struggle with temporal dependencies and require large amounts of labeled data to avoid overfitting. CLSSA-EDL addresses these limitations by incorporating LSTM networks within the ensemble to capture both spatial and temporal features, resulting in better performance on ECG signal classification.

D. LSTM-CNN

The LSTM-CNN model achieved 98.10% $accu_y$, 97.50% $sens_y$, 98.95% $spec_y$, and 89.30% F_{score}. The combination of LSTM and CNN leverages the strengths of both models, capturing spatial features with CNNs and temporal patterns with LSTMs. This hybrid approach significantly enhances performance. However, this approach has increased complexity and computational cost due to the integration of two different types of neural networks. CLSSA-EDL enhances this approach by optimizing the ensemble model's hyperparameters and architecture, ensuring a more efficient and accurate classification process.

E. ResNet

The ResNet model achieved 99.06% $accu_y$, 93.21% $sens_y$, 98.97% $spec_y$, and 95.81% F_{score}. The deep architecture and skip connections of ResNet help learn complex patterns and mitigate the vanishing gradient problem, leading to high performance in classification tasks. However, ResNet requires significant computational resources and can be prone to overfitting if not properly regularized. The proposed CLSSA-EDL technique, with its ensemble approach, provides similar benefits in terms of deep feature extraction while also enhancing robustness and generalization through comprehensive learning and optimization strategies.

F. Modified U-Net

The modified U-Net model achieved 97.32% $accu_y$, 94.44% $sens_y$, 98.78% $spec_y$, and 89.96% F_{score}. U-Net, designed for image segmentation, captures detailed features and boundaries well. Its architecture is beneficial for tasks requiring precise localization and segmentation. Although it is effective for segmentation, it may not be as efficient for classification tasks where deep feature hierarchies are more crucial. CLSSA-EDL leverages the strengths of deep classifiers such as ResNet and ensemble learning, providing a more targeted and efficient approach for ECG signal classification.

G. Proposed CLSSA-EDL

The proposed CLSSA-EDL model achieved 99.33% $accu_y$, 99.00% $sens_y$, 99.50% $spec_y$, and 98.99% F_{score}. The CLSSA-EDL technique integrates SSA with ensemble deep learning, optimizing hyperparameters and model structures to achieve superior performance. Its ability to adapt and fine-tune the ensemble model ensures high accuracy, sensitivity, specificity, and F-score. This approach enhances exploration and exploitation during optimization, leading to better solutions. In addition, its ensemble approach aggregates predictions from multiple models, improving robustness and reducing the risk of overfitting. Furthermore, its hyperparameter optimization ensures that the model is fine-tuned for the specific task, maximizing performance. The superior performance of CLSSA-EDL across all metrics demonstrates its effectiveness and robustness compared to existing methods. Its ability to capture spatial and temporal features, combined with optimized hyperparameters and model structures, makes it particularly well-suited for ECG signal classification.

H. Relationship Between Research Survey and Comparison Targets

This study serves several critical purposes:

- Identifying state-of-the-art techniques: Key models were identified, which represent the state-of-the-art ECG signal classification. These models were chosen as benchmarks for comparison to ensure that the evaluation is comprehensive and relevant.
- Highlights gaps and challenges: The survey reveals the strengths and weaknesses of existing methods, guiding the development of the CLSSA-EDL technique to address them. For instance, the proposed method addresses issues such as overfitting in ANN models, the complexity of LSTM-CNN hybrids, and the computational demands of ResNet.
- Provides a baseline for comparison: The literature surveyed establishes a baseline for performance metrics such as accuracy, sensitivity, specificity, and F-score. This baseline is essential to demonstrate the improvements achieved by the CLSSA-EDL technique.
- Justifies methodological choices: This study highlighted effective strategies and techniques used in previous studies. For example, combining LSTM and CNN in hybrid models inspired the inclusion of LSTM networks in the proposed ensemble approach.

V. CONCLUSION

This study presents a novel technique, called CLSSA-EDL, for ECG signal classification in the IoT healthcare environment. The CLSSA-EDL approach achieves remarkable performance with an accuracy of 98.7%, sensitivity of 97.5%, and specificity of 99.1%. These results demonstrate the effectiveness of the proposed method in accurately detecting and classifying ECG signals. The contributions of this work are significant. First, integrating DenseNet201 for feature extraction, optimized through CLSSA, represents a major advance in capturing intricate patterns in ECG signals. Second, the ensemble model combining SAE, GRU, and LSTM enhances classification performance by effectively capturing both spatial and temporal features in the data. The implications of the findings are substantial for IoT healthcare environments. This approach outperformed recent algorithms in accuracy, sensitivity, and specificity compared to existing methods, demonstrating superior performance and reliability. This highlights the potential of the proposed technique to set a new standard in ECG signal classification and IoT healthcare applications. Future work will focus on further optimizing the model and exploring its application to other biomedical signal classification tasks. The promising results of this study encourage the continued development and implementation of advanced AI-driven techniques in healthcare.

ACKNOWLEDGMENTS

This paper is derived from a research grant funded by the Research, Development, and Innovation Authority (RDIA), Kingdom of Saudi Arabia, with grant number 13382-psu-2023-PSNU-R-3-1-EI-. The authors would like to acknowledge the support of Prince Sultan University, Riyadh, Saudi Arabia in paying the article processing charges of this publication. This research is supported by the Automated Systems and Soft Computing Lab (ASSCL), Prince Sultan University, Riyadh, Saudi Arabia. In addition, the authors wish to acknowledge the editor and anonymous reviewers for their insightful comments, which have improved the quality of this publication.

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