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Original Article

An Ensemble of Deep Learning with Optimization Model for Activity Recognition in the Internet of Things Environment

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Abstract *- Lately, IoT (Internet of Things) based m-healthcare application is rising to give real-time servicing in the present global lifestyle. Cloud-based healthcare architecture provides best results than traditional approaches. Currently, Integrating IoT devices in the medical environment plays a crucial role in handling a massive amount of medical data. Thus, researcher workers aimed to automate the procedure of diagnosis and detecting diseases with the help of could computing techniques. Furthermore, deep learning and machine learning techniques used in the healthcare field allow healthcare professionals to focus, monitor, highlight and diagnose the region of the problem and present the accurate and required solution in a short duration. Therefore, this paper presents Artificial Bee Colony Optimization with Ensemble Deep Learning based Disease Diagnosis (ABCO-EDLDD) in the IoT atmosphere. The proposed ABCO-EDLDD procedure effectively identifies the existence of diseases in the IoT atmosphere. At the initial stage, the ABCO-EDLDD technique transforms the input data gathered by the IoT devices in different ways. Next, the ABCO algorithm is utilized for the optimal selection of feature subsets. For disease classification, an ensemble of DL models such as Gated Recurrent Unit (GRU), Long Short Term Memory (LSTM), and Bidirectional Long Short Term Memory (BiLSTM) model. Finally, the RMSProp optimizer is used for the optimum tuning of the DL models. The experimental evaluation of the ABCO-EDLDD algorithm takes place by implementing two medical datasets: the HAPT dataset and the heart disease dataset. The experimental results reported the improved performance of the ABCO-EDLDD procedure over other current techniques.*

Keywords *- Healthcare, Internet of Things, Deep learning, Disease diagnosis, Feature selection, Ensemble learning.*

1. Introduction

The Internet of Things (IoT) can be termed as a network of Internet-connected physical gadgets that communicate with one another through the Internet. Cloud computing (CC) distributes several resources to users through the Internet, like storage, software, networking, etc. IoT combined with CC can raise the repository of resources and performance abilities to the fullest. CC is leveraged as a front-end to access the IoT platform [1, 2]. The consumerization of the medical system has increased by advancing and cheering persons to use linked gadgets like hand-held devices, smartphones, and wearable gadgets to live in their comfort zone. IoT was the revolutionary innovation that solved the difficulties of interoperability to change the way healthcare was presented [3], driving enhanced outcomes, making healthcare accessible, and raising quality. The IoT equips person-centred infrastructures for producing improved results. The significant IoT applications were the detection of smart homes, the recognition of patient disease, and the recognition of an earthquake [4]. The significant technologies employed for IoT transmission were Zigbee, WiFi, RFID, Bluetooth, etc. The healthcare system must be devised to manage a massive quantity of patient data [5]. The cloud serves a crucial role in the health care system to handle the enormous volume of information. Difficulties were rising because of the increasing use of the healthcare system. IoT-Cloud-related healthcare systems have several benefits, like effective patient monitoring, enhanced patient report management, easy access to patient reports, cost-saving, etc.

The monitoring system devised by two technologies can simply monitor and manage patients on a large area of land. The IoT platform comes with Claude's atmosphere for raising its computational power. This can be made by including smaller gadgets on the user side in such a way that a single set of computations can be made initially and not every server-side analysis. Hence, integrating the IoT mechanism and cloud platform was planned to raise calculational power. A combination of a suite of Freeware and IoT cloud-related applications was superior in efficiency associated with a cloud-based atmosphere [6]. Emerging applications like commerce, military, and medical applications are employed in this model.

In particular, IoT-based cloud technologies were very appropriate for the use of medical services. For instance, it can be employed to monitor and access reports in any distant place. IoT-based health systems were beneficial for collecting essential data, which includes recurrent deviations to timely health variables and upgrading the intensity of medical variables over a standard time frame [7]. Moreover, sensor readings and IoT gadgets relevant to medical variables were employed efficiently for detecting illness at a suitable period and before severe circumstances were attained [8]. Machine learning (ML) serves a significant role in the process of decision-making. It even controls an enormous volume of data. The Data Analysis Matching Procedure was employed to assign this information to accurate areas like predicting the speed and volume of standard data for NN modelling and classification [9]. Data is generated from various sources; hence it is significant for analyzing the program and is substantial for advancing techniques that control data properties [10]. By the way, in this study, an ML technique is implemented that endures the process of artificial intelligence (AI) mapping data into two classes, like "affected" and "normal".

This paper presents Artificial Bee Colony Optimization with Ensemble Deep Learning based Disease Diagnosis (ABCO-EDLDD) in the IoT environment. The suggested ABCO-EDLDD technique effectively transforms the input data gathered by IoT devices in different ways. Followed by the ABCO algorithm is utilized for the optimal selection of feature subsets. For disease classification, an ensemble of DL models such as Gated Recurrent Unit (GRU), Long Short Term Memory (LSTM), and Bidirectional Long Short Term Memory (BiLSTM) model. Lastly, the RMSProp optimizer is used for the optimum tuning of the DL models. The experimental evaluation of the ABCO-EDLDD algorithm takes place by implementing two medical datasets: the HAPT dataset and the heart disease dataset.

2. Related Works

The author in [11] established an Online Medical Decision Support System (OMDSS) for the anticipation of Chronic Kidney Disease (CKD). The established methodology encompasses a sequence of steps, namely data classification, gathering, and preprocessing of the medicinal dataset to anticipate CKD. For categorization, Logistic Regression (LR) mechanism has been implemented for categorizing the info instance into CKD and non-CKD. Furthermore, in tuning the parameter of LR, the adaptive learning rate optimizing technique and Adaptive Moment Estimation (Adam) model have been used in this work. The author in [12] the information gathered from the IoT sensor pertaining to coronary ailment risk anticipation is subjected to the information preprocessing task of information filtering and cleaning at the Cloud level. The resultant info is transmitted to the Fuzzy Information Systems (FISs) for the primary duty of categorization; lastly, the presented BiLSTM mechanism has been applied for precisely forecasting the danger of coronary ailment in patients.

The author in [14] developed an extensible cloud-based teleophthalmology context through the Internet of Medical Things (IoMT) for the diagnoses of AMD. In this work, the patient wears a head-mounted camera (OphthoAI IoMT headset) to transmit the retinal fundus photos to their private and secure storing cloud drive for predictive progression analysis and customized disease severity detection. The introduced AMD-ResNet CNN with 152 layers would examine the imagery for recognizing and defining the ailment severity of AMD. In [15], the author proposed a novel healthcare monitoring scheme for monitoring disease levels by forecasting the disease based on the original dataset gathered from the patient accessible in a remote location. Furthermore, a secure data storage mechanism has been proposed to store patient information in the cloud server securely. At present, the study introduced two new cryptographic systems to perform encryption and decryption.

In [16], a rural health surveillance procedure uses a lightweight block encryption approach to provide confidentiality for medicinal and healthcare info in a cloud-based IoT framework. In the presented method, the patient's health status was specified by anticipating critical circumstances via a data mining technique for investigating the biological info detected by smart medicinal IoT devices. The lightweight secured block encryption technique ensured the patient's delicate information became secure. Lightweight block encryption procedure has a vital and efficient impact on these sorts of schemes due to the limited resource in the IoT platform.

Tuli et al. [18] developed a novel construction called HealthFog to incorporate ensemble DL in Edge calculating equipment and installed it for real-time usages of automatic coronary ailment evaluation. HealthFog brings healthcare as fog services with IoT equipment and efficaciously handles the info of coronary patients that comes as a user request. Fog-aided cloud architecture, FogBus, is utilized for deploying and testing the accomplishment of the presented method with respect to networking bandwidth, power utilization, jitter, latency, implementation time, and precision. Juyal et al. [19] developed a novel 'Intelligent' concept of a Skin Monitoring Device that empowers affected individuals in remote areas to detect skin ailments remotely. The introduced technique contains cloud and AI-based IoTs under which CNN analyses the ailment anticipations and medicinal imageries.

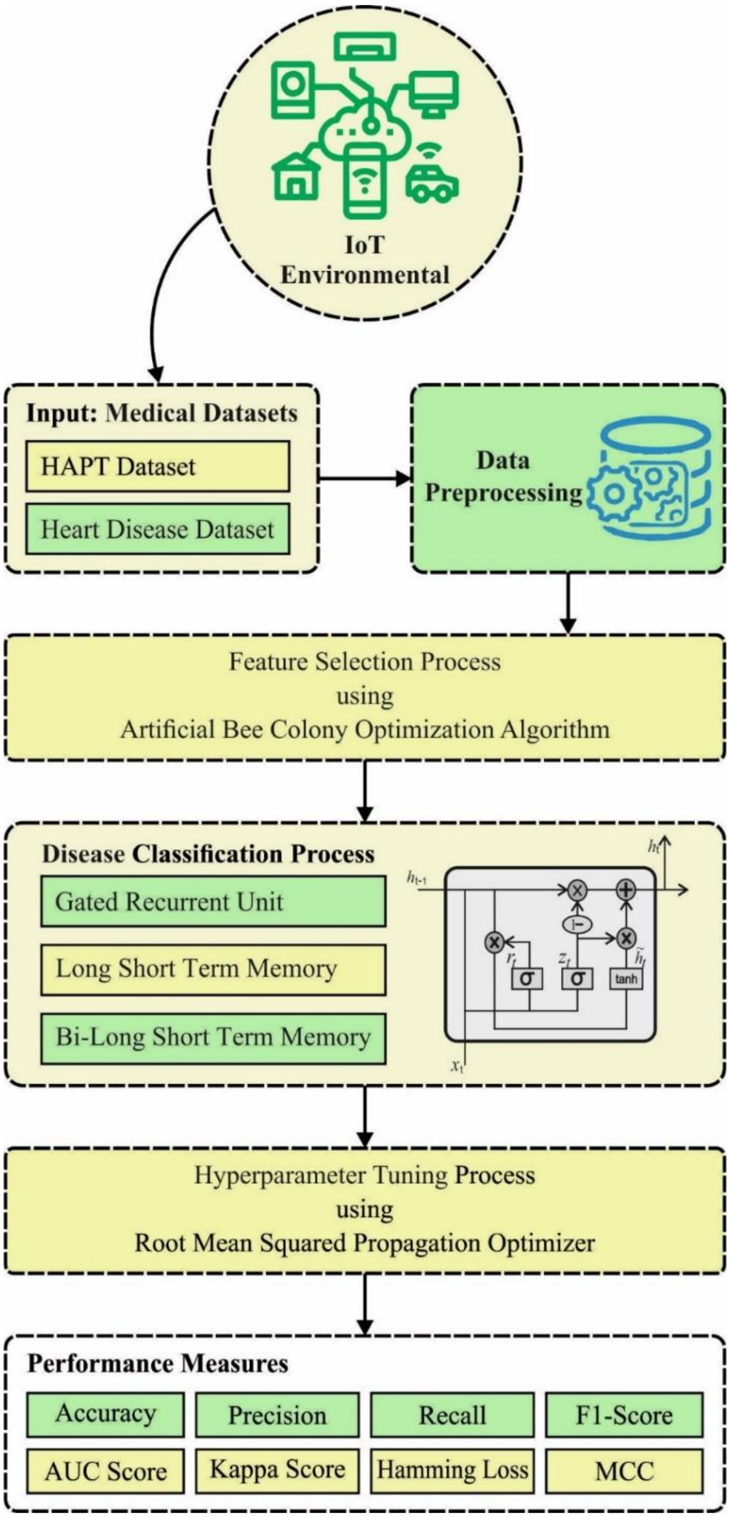

Fig. 1 Working process of ABCO-EDLDD model

3. The Proposed Model

This paper has established a new ABCO-EDLDD procedure for disease analysis in the IoT atmosphere. It mainly detects the occurrence of diseases in the IoT environment. It encompasses several sub-processes, namely data preprocessing, feature selection using the ABCO algorithm, ensemble DL classification, and RMSProp-based hyperparameter tuning. Figure 1 shows the working procedure of the presented prototype.

3.1. Data Preprocessing

In this study, the IoT devices collect medical information, which is initially preprocessed to make it compatible with ML-based classification. The data preprocessing takes place in different ways, as listed below.

- Data preparation,
- Null values removal,
- Categorical to numerical,
- Class labelling, and
- Standard scaling

3.2. Feature Selection using ABCO Algorithm

For the optimal selection of features, the ABCO algorithm is exploited in this work. ABCO is a metaheuristic approach which optimizes the problem of unremitting space. It mimics the foraging behaviours of bees. This technique comprises of few essential elements, namely unemployed bees, a food source (FS), and employed bees [20]. In this work, half of the bees are employed bees, and the remaining are onlooker bees (OBEEs).

Every FS represent an employed bee that uses its own FS and returns to the hive to put across data regarding its FS with other bees. Every OBEE follows the dance of the bees and selects the FS. Based on this approach, the nectar amount of a source signifies the *fitn* of the resolution, and an FS exemplifies a possible solution (FS location) of the problem. The ABCO steps are given below:

Step 1: Initialization: SN FS position is produced at random. SN signifies the number of FS positions or employed bees. Every FS, X_i, whereas $i \in \{1,2,\cdots,SN\}$, D represent dimensional vectors that represent the number of variables to resolve the optimization problems. In general, the final FS position can be generated at random as follows:

$$X_i^j = X_{\min}^j + rand(0,1)\left(X_{\max}^j - X_{\min}^j\right) \qquad (1)$$

Whereas $j = 1,2, \dots, D$; X_{max}^j and X_{min}^j represent the maximal and minimal values for the j^{th} parameter of the problem; rand shows the uniformly distributed random number ranges from zero to one.

Step 2: Nectar amount (*fitn* value) assessment of the FS: In this phase, the *fitn* (nectar amount) of every FS is calculated.

Step 3: Employed bee: Here, every bee is transferred to the FS and searches for a new FS enjoying an additional nectar amount (*fitn*) of its FSs amongst his neighbourhood. For every employed $beeX_i$, neighbour FS location that is V_i ad can be evaluated as follows:

$$y_i^{jrand} = X_i^{jrand} + rand[-1,1].(X_i^{jrand} - X_k^{jrand}) \qquad (2)$$

Whereas X_k represents the randomly chosen FS, $k \in \{1,2,\dots,SN\}$ is randomly specified and should be distinct from i, $jrand \in \{1,2,\cdots,D\}$ represent the random value, and $rand[-1,1]$ indicates a random number amongst $[-1, 1]$.

Step 4: Quality (*fitn* value) selection and evaluation: in this phase, the *fitn* of new FSs is higher than the existing FS, then bee store this new FS location (solution) and leave the older place.

Step 5: Onlooker bee: each employed bee completes the search process; employed bees transmit the nectar amount of the FSs. Once the OBEE perceives an FS, it assesses the quality data attained through employed bees and identifies an FS X_i with the probability value p_i associated with the quality.

For every X_i, the p_i probability value can be evaluated, where $fitness_i$ shows the nectar amount of FS i appreciated by the employed bee. To do this, a random number between zero and one is produced and related to th$e$ p_i probability value. If the probability value of the FS, which is calculated based on Eq. (3), is higher than these random values, this FS is selected for the OBEE that explores new FSs.

$$p_j = \frac{fitness_i}{\sum_{n=1}^{SN} fitness_n} \qquad (3)$$

Step 6: Memorizing the better FS; the better FS have, the maximum *fitn* is remembered.

Step 7: SBEE procedure: in this phase, a new FS is indicated as an SBEE and interchanged with the abandoned FS. For these processes, a counter, which is named exceed the limit, is utilized for every bee in the swarm. When there exists a bee, its counter values exceed maximal limits, it leaves the FS and pursues a new FS [21]. To search for a novel FS, an SBEE applies Eq. (1).

Steps 3 to 7 are iterated until an ending condition is reached. The better solution is the (sub) optimal solution for the problems. The *fitn* function is intended to balance between the number of selected features in every classification accuracy (maximum) and solution (minimum) attained by using the chosen component, Eq. (10) characterizes the *fitn* function to assess the solution.

$$Fitness = \alpha\gamma_R(D) + \beta\frac{|R|}{|C|} \qquad (4)$$

Whereas $\gamma_R(D)$ characterizes the categorization fault rate. $|R|$ represents the cardinality of the chosen subset, and $|C|$ indicates the total amount of aspects in the data, α and β show the two parameters corresponding to the significance of categorization quality and subset length. $\in [1,0]$ and $\beta = 1 - \alpha$.

3.3. Ensemble DL-based Classification

In this work, an ensemble of three DL models takes place for disease classification. The DL approach is combined, and the optimal results are selected by a weighted voting algorithm in the presented model [22]. Assumed the n amount of classes and D base classifier to vote, the predictive class c_k of weighted voting for each instance, k, can be specified as follows:

$$c_k = \arg\max_j \sum_{\mathrm{i}=1}^{D}\left(\Delta_{\mathrm{ji}} \times w_{\mathrm{i}}\right) \tag{5}$$

From the expression, Δ_{ji} characterizes the binary variable. Once the i-th base classifier categorizes the k instances into j-th classes, then $\Delta_{\mathrm{ji}} = 1$; or else, $\Delta_{\mathrm{ji}} = 0$. w_{i} represents the weight of the i-th base classifier.

$$Acc = \frac{\sum_k \{1 | c_k \text{is the true class of instance } k\}}{\text{Size of test instances}} \times 100\% \tag{6}$$

3.3.1. GRU Model

GRU is a kind of LSTM networking that inherits the merits of RNN: it efficiently models more extended dependency data, automatically learns features, and is used for prediction [24]. Intuitively, the input gate and forget gate in LSTM will be incorporated as reset gates in GRU that determine how to combine the input dataset with the preceding time. Other gates in GRU are called update gates; it defines data from the last time that can be saved at the current time. These variations make GRU have fast training speed and fewer parameters and need fewer data for efficiently generalizing the system.

$$z_n = \sigma(W_z \cdot [h_{n-1}, x_n]) \tag{7}$$

$$r_n = \sigma(W_r \cdot [h_{n-1}, x_n]) \tag{8}$$

$$\overline{h}_n = \tanh\,(W \cdot [r * h_{n-1}, x_n]) \tag{9}$$

$$h_n = (1 - z_n) * h_{n-1} + z_n * \overline{h} \tag{10}$$

Eqs. (4) and (5) illustrate how the update gate z_n and reset gate r_n are assessed in GRU neurons. W_z shows the weight of z_n, W_r characterizes the weight of r_n, and 0 indicates the sigmoid function. $[h_{n-1}, x_n]$ specifies the sum of vector h_{n-1} and x_n. The largest value of z_n This signifies that data had been retained using existing cells, where less for the preceding cell. r_n suggests that when the value corresponds to 0, then data from the previous cell can be eliminated. Eq. (6) and (7) demonstrate the assessment of pending output value $\overline{h}$ and final output value h_n of GRU-NN. h_{n-1} shows the outcome from the prior cell, W characterizes the weight of z_n, and tanh implies a hyperbolic tangent function. $\overline{h}_n$ can be obtained by multiplying h_{n-1} of previous cells by r_n, along with x_n, multiplied with the W, and hyperbolic tangent function. h_n specifies the amount of two vectors. The former is accomplished by multiplying z_n by $\overline{h}_n$ and later by multiplying $1 - z_n$ by h_{n-1}.

3.3.2. LSTM Model

RNN mechanism has been widely applied for predicting and analysing time series datasets. This technique often undergoes gradient vanishing issues from the training module. Hence, it is complicated to remember the prior data, like long dependence issues [25]. The LSTM model was introduced to handle these problems, which is the function of memory from the long span.

This method uses a gate control technique to adjust the data flow and systematically determines the number of received datasets retained from each time step. The basic LSTM unit's construction comprises three controlling gates (input, output, and forget gates) and storing units. x_z and h_z is corresponding to the input and hidden states of time z. f_z, i_z, and o_z describes the input, output, and forget gates. $\tilde{C}_z$ characterizes the candidate database to input that can be stored, and the amount of storage depends on input gates.

$$f_z = \sigma\left(W_f \cdot [h_{z-1}, x_z] + b_f\right) \tag{11}$$

$$i_z = \sigma(W_i \cdot [h_{z-1}, x_z] + b_i) \tag{12}$$

$$o_z = \sigma(W_o \cdot [h_{z-1}, x_z] + b_o) \tag{13}$$

$$\tilde{C} = \tanh\,(W_C \cdot [h_{z-1}, x_z] + b_C) \tag{14}$$

$$C_z = f_z \cdot C_{z-1} + i_t \cdot \tilde{C} \tag{15}$$

$$h_z = o_z \cdot \tanh\,(C_z) \tag{16}$$

From the expression, W_f, W_i, W_o, and W_c correspondingly show the weight matrices of forget, input, output and update state. b_f, b_i, b_o, and b_c indicate the bias vector of input, output, forget and update state. x^z shows the time series dataset of prevailing time interval z, and h_{z-1} refers to the ensuing memory unit from the prior time interval $z - 1$.

3.3.3. BiLSTM Model

The forward and reverse context representation can be represented as $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ are interconnected with the long vector, and the combined output is the depiction of the existing time to the input:

$$h_t = \overrightarrow{h_t} \oplus \overleftarrow{h_t} \tag{17}$$

Lastly, the output $[h_1, \dots h_i, \dots h_m, l_1, \dots l_j \dots l_n]$ of the entire sentence is attained, where h_i and l_j shows the output of words and emoticons correspondingly.

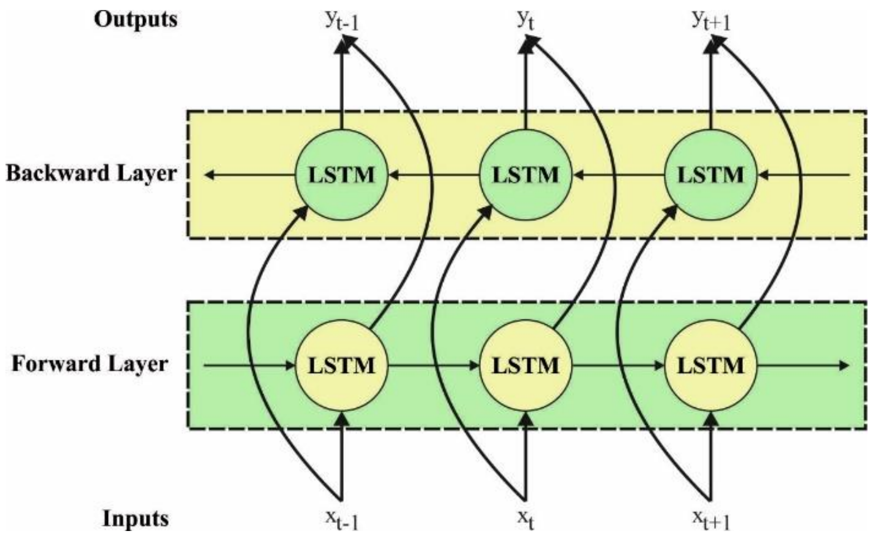

Fig. 2 Structure of BiLSTM model

Furthermore, set each intermediate layer in BiLSTM for returning the whole output sequences, thus guaranteeing that the result of every hidden layer preserves the long-distance data. The representation of BiLSTM is demonstrated in Figure 2.

3.4. Hyperparameter Tuning

At the final stage, the RMSProp optimizer [26] is used for optimum hyperparameter tuning of the DL models. The RMSprop optimizer limits the oscillation in the vertical direction. Consequently, it increases the learning rate, and the algorithm takes large Step-in the horizontal direction converging faster. The RMSprop calculation is demonstrated below. The momentum value can be represented as beta and is generally fixed at 0.9.

$$v_{dw} = \beta \cdot v_{dw} + (1-\beta) \cdot dw^2 \tag{18}$$

$$v_{db} = \beta \cdot' v_{dw} + (1-\beta) \cdot db^2 \tag{19}$$

$$W = W - \alpha \cdot \frac{dw}{\sqrt{v_{dw}}+\varepsilon} \tag{20}$$

$$b = b - \alpha \cdot \frac{db}{\sqrt{vdb}+\varepsilon} \tag{21}$$

In backward propagation, dW and db are used to upgrade W and b parameters in the following:

$$W = W - learning\ rate\ * dW \tag{22}$$

$$b = b - learning\ rate\ *\ db \tag{23}$$

In RMSprop, rather than utilizing dW and db individually for all the epochs, the exponentially weighted average of the square of dW and db has been considered.

$$S_{dW} = \beta^* S_{dW} + (1-\beta)^* dW^2 \tag{24}$$

$$S_{db} = \beta^* S_{db} + (1-\beta)^* db^2 \tag{25}$$

From the expression, beta β' is an additional hyperparameter and takes a value from 0 to 1. The novel weighted average is generated through weights, the average of the preceding value, and the existing value square. Afterwards, evaluating the exponentially weighted average, update the parameter as follows.

$$W = W - learning\ rate\ * dW/sqrt(S) \tag{26}$$

$$b = b - learning\ rate * db/sqrt(S) \tag{27}$$

S_{dw} is reasonably lesser such that divide it by dW. S_{db} is reasonably larger such that db with a comparatively large number slows down the update on the vertical dimension.

4. Performance Validation

The established model is duplicated by implementing the Python tool. In this segment, the investigational validation of the ABCO-EDLDD prototype takes place by employing two datasets, namely the HAR dataset [27] with classes of WALKING (0), WALKING_UPSTAIRS (1), WALKING_DOWNSTAIRS (2), SITTING (3), STANDING (4), LAYING (5), STAND_TO_SIT (6), SIT_TO_STAND (7), SIT_TO_LIE (8), LIE_TO_SIT (9), STAND_TO_LIE (10), LIE_TO_STAND (11) and heart disease (HD) dataset with classes of Presence and Absence [29].

In Figure 3, the FS outputs of the ABCO-FS approach on the HAR database are provided. The picture indicated that the ABCO-FS algorithm had obtained efficacious convergence with increased iterations.

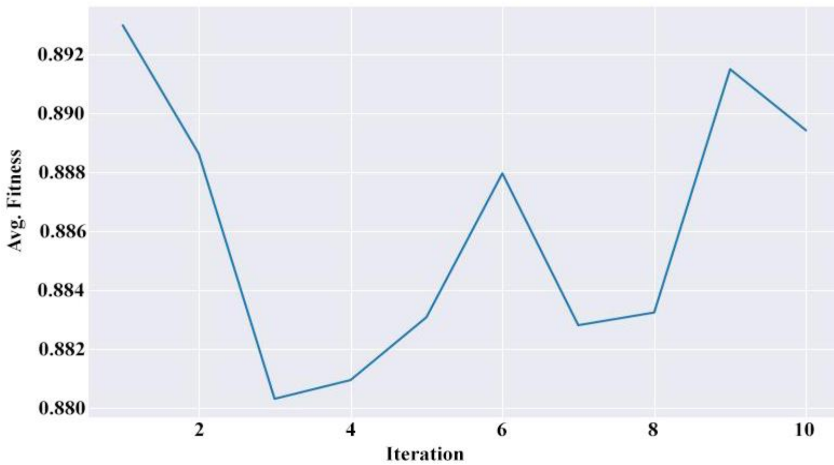

Fig. 3 Feature selection convergence graph on HAR dataset

Predicted Value \ Actual Value	0	1	2	3	4	5	6	7	8	9	10	11
0	1719	1	2	0	0	0	0	0	0	0	0	0
1	0	1544	0	0	0	0	0	0	0	0	0	0
2	2	3	1402	0	0	0	0	0	0	0	0	0
3	0	0	0	1726	75	0	0	0	0	0	0	0
4	0	0	0	56	1923	0	0	0	0	0	0	0
5	0	0	0	1	0	1957	0	0	0	0	0	0
6	0	0	0	0	0	0	69	0	0	0	1	0
7	0	0	0	0	0	0	0	33	0	0	0	0
8	0	0	0	0	0	0	0	1	105	0	1	0
9	0	0	0	0	0	0	0	0	0	81	0	4
10	0	1	0	1	0	0	1	0	2	0	133	1
11	0	0	0	0	0	1	0	0	0	9	1	73

Fig. 4 Confusion matrix of ABCO-EDLDD model on HAR dataset

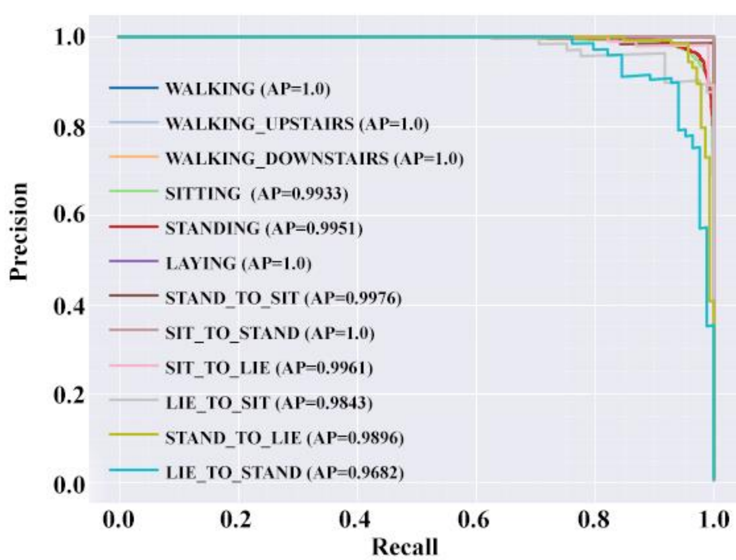

Fig. 5 PR curve of ABCO-EDLDD model on HAR dataset

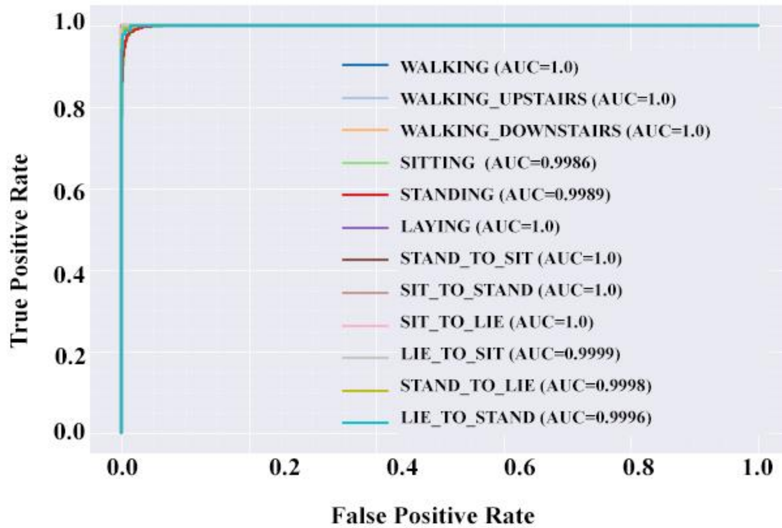

Fig. 6 ROC curve of ABCO-EDLDD model on HAR dataset

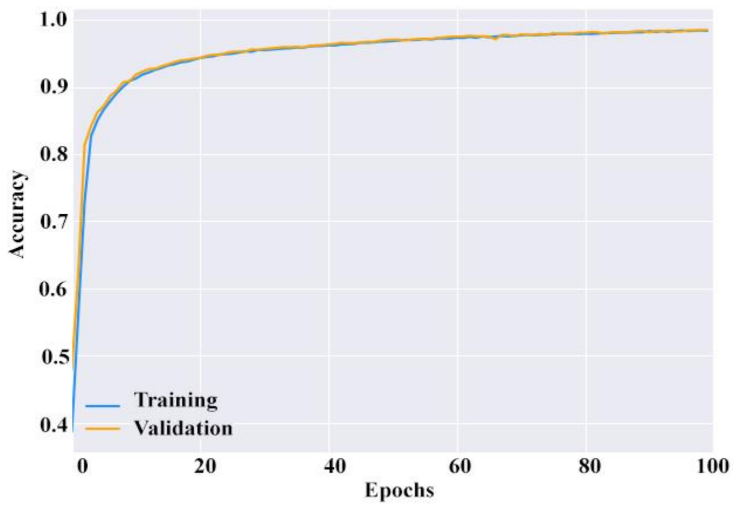

Fig. 7 TACC and VACC of ABCO-EDLDD model on HAR dataset

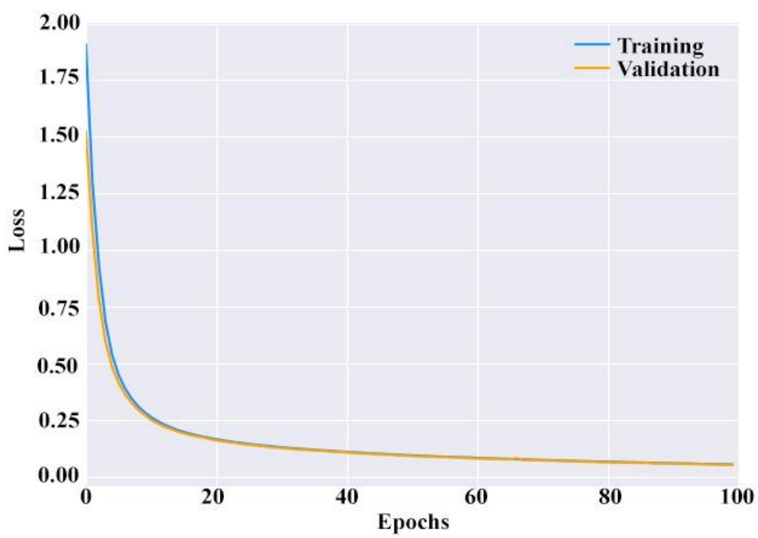

Fig. 8 TLS and VLS of ABCO-EDLDD model on HAR dataset

Fig. 9 Feature selection convergence graph on HD dataset

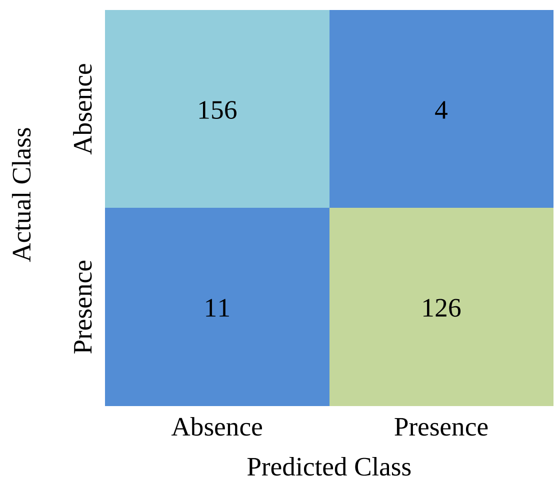

Fig. 10 Confusion matrix of ABCO-EDLDD model on HD dataset

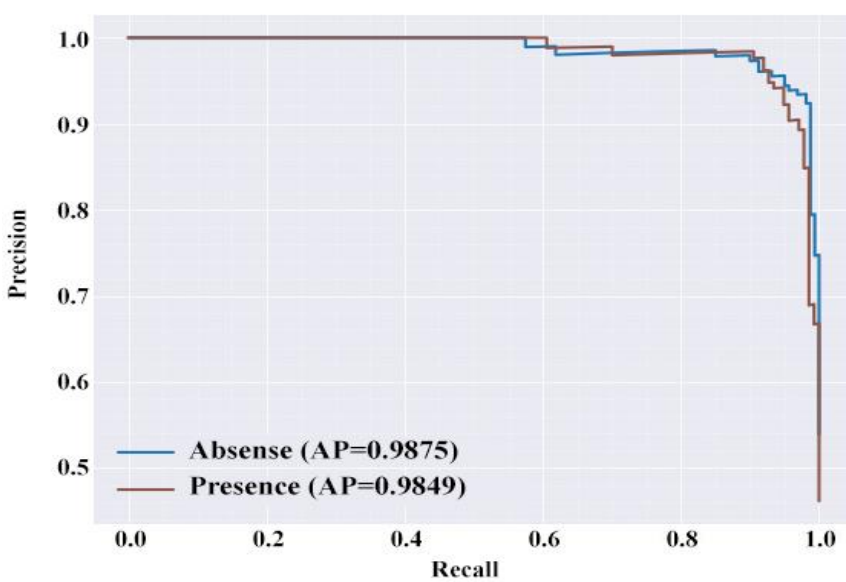

Fig. 11 PR curve of ABCO-EDLDD model on HD dataset

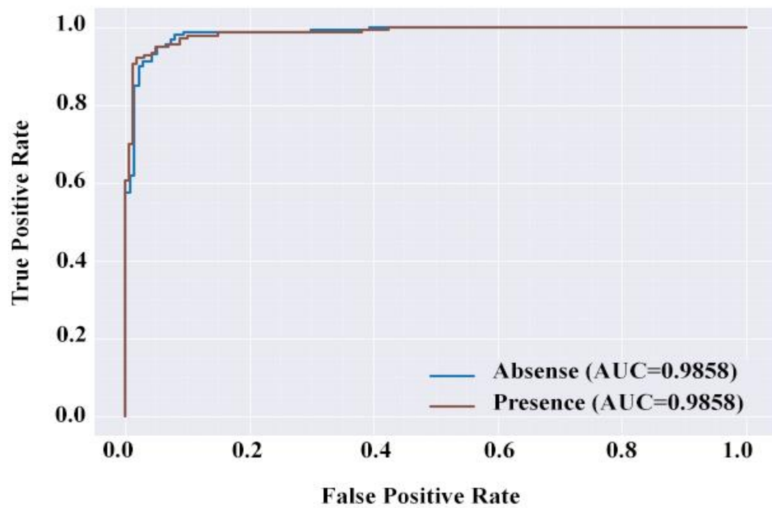

Fig. 12 ROC of ABCO-EDLDD model on HD dataset

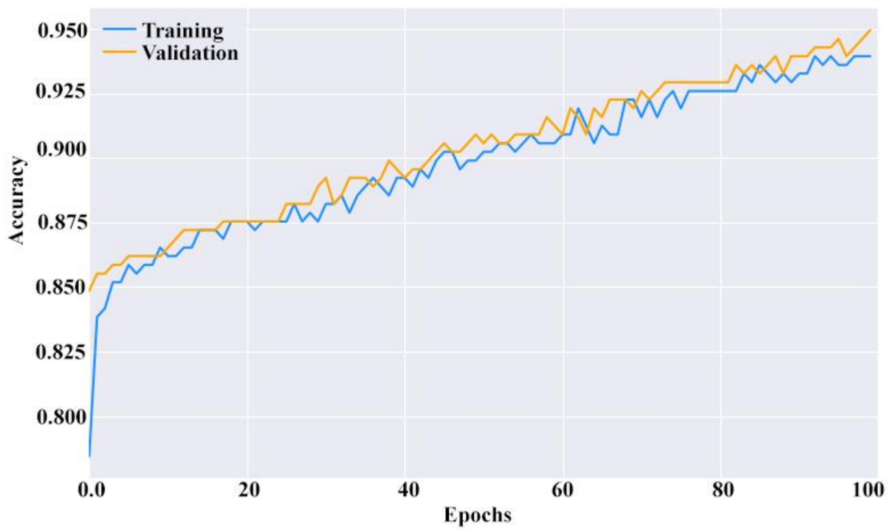

Fig. 13 TACC and VACC of ABCO-EDLDD model on HD dataset

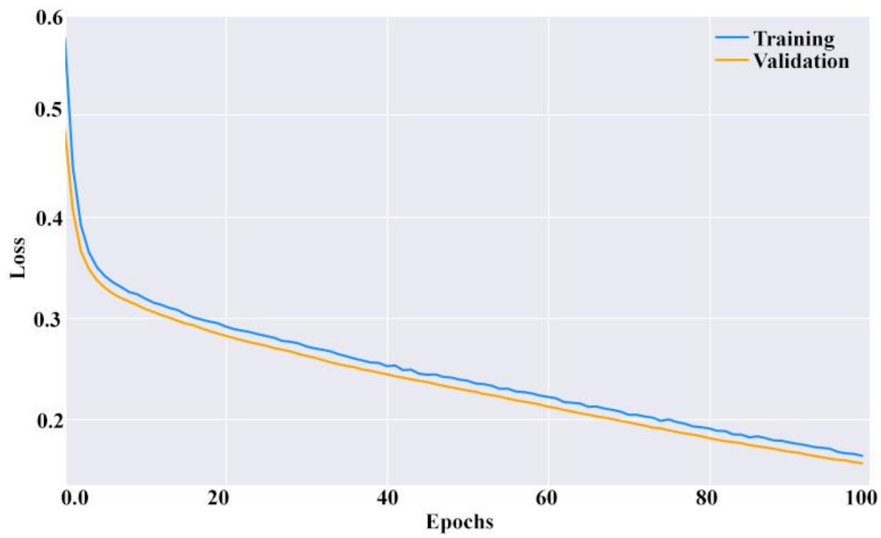

Fig. 14 TLS and VLS of ABCO-EDLDD model on HD dataset

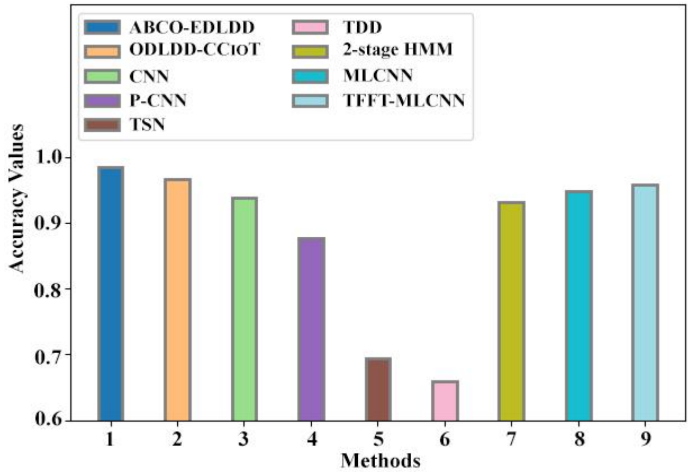

Fig. 15 Comparative accu$_y$ of ABCO-EDLDD technique with recent models on HAR dataset

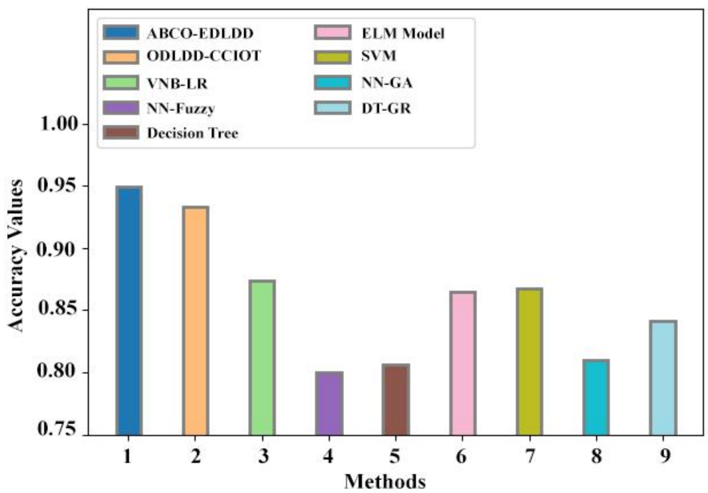

Fig. 16 Comparative accu$_y$ of ABCO-EDLDD technique with recent models on HD dataset

Table 1. Outcome evaluation of proposed model on HAR and heart disease dataset

Measures	HAR Dataset	Heart Disease Dataset
Accuracy	98.50	94.95
Precision	97.29	95.17
Recall	97.25	94.74
F1-Score	97.25	94.90
AUC Score	99.97	98.58
Kappa Score	98.23	89.80
Hamming Loss	01.50	05.05
MCC	97.11	89.90

The confusion matrix of the ABCO-EDLDD approach under the HAR dataset is demonstrated in Figure 4. The picture depicts that the ABCO-EDLDD approach has properly categorized all different types of human activities.

A precise precision-recall investigation of the ABCO-EDLDD model under the trial HAR database is given in Figure 5. The outcomes exhibited by the ABCO-EDLDD algorithm have enhanced precision-recall values under total categories.

The elaborated ROC study of the ABCO-EDLDD technique under the trial HAR dataset is demonstrated in Figure 6. The results indicated that the ABCO-EDLDD approach exhibited its ability to classify diverse categories under the trial dataset.

The TACC and VACC of the ABCO-EDLDD technique are examined on HAR dataset achievement in Figure 7. The outcomes showed that the ABCO-EDLDD method had precipitated accomplishment with amplified outcomes of

TACC and VACC. It is evident that the ABCO-EDLDD algorithm has attained the most significant TACC outputs.

The VLS and TLS of the ABCO-EDLDD technique are examined on HAR dataset accomplishment in Figure 8. The results displayed that the ABCO-EDLDD procedure has shown better achievement with lesser results of TLS and VLS. It is seen that the ABCO-EDLDD approach has displayed mitigated VLS outputs.

In Figure 9, the FS results of the ABCO-FS method on the HD dataset are provided. The figure shows that the ABCO-FS approach has gained effective convergence with increased iterations. The confusion matrices of the ABCO-EDLDD method under the HD dataset are given in Figure 10. The figure depicted that the ABCO-EDLDD procedure has properly categorized two classes, i.e. presence and absence of HD.

A precise precision-recall analysis of the ABCO-EDLDD method under the trial HD database is given in Figure 11. The outputs displayed by the ABCO-EDLDD technique have an improved value of precision-recall under all categories.

The elaborated ROC study of the ABCO-EDLDD approach under the trial HD dataset is shown in Figure 12. The outputs signified that the ABCO-EDLDD procedure had shown its capability in categorizing diverse categories under the trial dataset.

The TACC and VACC of the ABCO-EDLDD procedure are examined on HD dataset achievement in Figure 13. The outcomes show that the ABCO-EDLDD algorithm has an enhanced accomplishment with augmented results of TACC and VACC. It is evident that the ABCO-EDLDD algorithm has attained the most significant TACC outputs.

The TLS and VLS of the ABCO-EDLDD method are examined on HD dataset accomplishment in Figure 14. The outcomes depict that the ABCO-EDLDD algorithm has shown better achievement with lesser results of TLS and VLS. It is noted that the ABCO-EDLDD method has shown mitigated VLS outputs.

Table 1 provides an overall classification result of the ABCO-EDLDD technique under both datasets. The investigation indicated that the ABCO-EDLDD technique had gained effective outcomes under HAR and HD datasets. For example, on the HAR database, the ABCO-EDLDD method has obtained $accu_y$ of 98.50%, $prec_n$ of 97.29%, $reca_l$ of 97.25%, $F1_{score}$ of 97.25%, AUC_{score} of 99.97%, kappa of 98.23%, HL of 1.50%, and MCC of 97.11%. Meanwhile, on the HD dataset, the ABCO-EDLDD technique has provided $an\, accu_y$ of 94.95%, $prec_n$ of 95.17%, $reca_l$ of 94.74%, $F1_{score}$ of 94.90%, AUC_{score} of 98.58%, kappa of 89.80%, HL of 5.05%, and MCC of 89.90%.

An elaborated relative study of the ABCO-EDLDD technique with current prototypes [30-33] on the HAR database is demonstrated in Figure 15. The investigational values indicated that the TSN and TDD models had revealed reduced $accu_y$ values of 0.6940 and 0.6590 appropriately. Then, the P-CNN prototype attained a slightly enhanced $accu_y$ of 0.8760 while the MLCNN and TFFT-MLCNN prototypes achieved closer $accu_y$ of 0.9479 and 0.9575, respectively. Although the ODLDD-CCIoT model has reached a reasonable $accu_y$ of 0.9662, the ABCO-EDLDD technique has shown maximum performance with $an\, accu_y$ of 0.9850.

A detailed relative study of the ABCO-EDLDD technique with current models on the HD database is shown in Figure 16. The investigational values indicated that the ABCO-EDLDD algorithm had shown the greatest achievement with an $accu_y$ of 0.9495. Contrastingly, the existing models such as ODLDD-CCIoT, VNB-LR, NN-Fuzzy, DT, ELM, SVM, NN-GA, and DT-GR prototypes have gained reduced outcomes with $accu_y$ of 0.9327, 0.8741, 0.8000, 0.8068, 0.8650, 0.8676, 0.8099, and 0.8410, respectively. From the elaborated outputs, it is established that the ABCO-EDLDD technique has shown the most significant achievement in disease diagnosis in the IoT environment.

5. Conclusion

In this research, we have established a new ABCO-EDLDD procedure for disease diagnosis in the IoT situation. It mainly detects the occurrence of diseases in the IoT environment. At the initial stage, the ABCO-EDLDD technique transformed the input data gathered by the IoT equipment in diverse ways. Moreover, the ABCO algorithm is utilized for the optimal selection of feature subsets. An ensemble of DL models, such as GRU, LSTM, and BiLSTM models, is used for disease classification. Finally, the RMSProp optimizer is used for optimum hyperparameter tuning of the DL models. The experimental evaluation of the ABCO-EDLDD procedure takes place by employing two medical databases: the HAPT dataset and the heart disease database. The investigational outputs reported the improved achievement of the ABCO-EDLDD algorithm over other current procedures. In future, the accomplishment of the ABCO-EDLDD process can be boosted by metaheuristic algorithms.

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