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HYPERPARAMETER OPTIMIZATION BASED DEEP LEARNING MODEL FOR MEDICAL DATA CLASSIFICATION IN INTERNET OF THINGS ENABLED CLOUD ENVIRONMENT

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ABSTRACT

Recently, the integration of internet of things (IoT) and advanced medicinal sensors can be contributed to improving the quality of healthcare services. In this way, the cloud and IoT technologies are completely utilized to design intelligent healthcare systems which can support real time applications by the use of artificial intelligence techniques. The recently developed deep learning (DL) approaches pave the way to design effective medical data classification models to diagnose diseases. With this motivation, this paper presents a new hyper parameter optimized DL technique for medical data classification in IoT enabled cloud environment. The proposed model enables the IoT devices to collect healthcare data and diagnose diseases in the cloud server. Primarily, the IoT devices are used for data acquisition and data preprocessing takes place to enhance the data quality. In addition, a convolutional neural network-long short term memory (CNN-BILSTM) method is employed for classification purposes, which identifies the presence of diseases or not. For boosting the classification performance of the CNN-BILSTM model, a black widow optimization (BWO) technique is applied to determine the optimal learning rate of the CNN-BILSTM model. A wide range of simulations take place on three benchmark medical datasets and the experimental results highlighted the promising efficiency of the proposed method over the other techniques.

Keywords: *Healthcare, Data classification, Cloud computing, IoT, Remote diagnosis, Deep learning, Learning Rate*

1. INTRODUCTION

In recent years, Wireless Sensor Networks (WSNs) have faced novel developments based on interfacing, applications, data computation, scalability, and interoperability [1]. Such innovations and technologies in Radio Frequency Identification (RFID), and cellular & wireless networks have placed a strong framework on the Internet of Things (IoT) [2]. It denotes a smart world of object, in which all the objects are linked to the Internet [3]. In IoT, each object is called an entity, which has digital identities and is remotely controlled, organized, and managed also has an opportunity to exceed the limitations. Because of the development in the growth of smart objects, IoT has improved most of the factors of their day-to-day life and keeps doing this with different ranges of intelligent, novel, and innovative applications [4].

Such application includes smart cities, smart healthcare, crowed sourcing, smart agriculture and crowd sensing, and so on.

Recently, healthcare is one of the increasing information technology to deliver smart systems intended for accelerating health treatment and diagnostics [5]. This system provides smart services to medical automation and health monitoring in diverse environments and contexts (offices, home, hospitals, etc.,), hence it allows to significantly reduce physicians visiting costs and a common improvement of patient's quality of care [6]. Thus, the devices for ubiquitous healthcare and improvement of smart medical together with wider

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diffusion of strong embedded hardware sensors has created the Internet of Medical Things (IoMT) significantly changes the way of approaching healthcare globally, hence the amount of healthcare devices utilizing wearable and IoT techniques are anticipated to attain around 162 million at the end of 2020. Data taken by the ingestible, mobility patterns, wearable, embedded sensor allows, device usage patterns to trace person behaviors and could be efficiently processed and collected for revealing crucial situations with the help of advanced AI) and ML or DL based methods.

The present times of healthcare are mainly based on the utilization of AI like data science and DL, i.e., progresses made in the fields [7]. Using this at earlier phase of analysis, detection, presentation, and management could be performed. The utilization of smart devices like edge devices, IoT, robots, drones, intelligent medical equipment, and webcam is helpful in pandemic situations [8]. Transfer learning as a domain adaptation proposes a novel resolution to the problem making it easier to the label structure and map feature distribution [9]. Identifying classification and activities via various sensor models are incorporated as innovative technologies for real time and autonomous behavior activities, analysis, observing of everyday life, rehabilitation, ambient supported for existing, elderly care, entertainment, and surveillance in smart homes [10]. Such sensors are pre-processed, and distinct feature sets such as wavelet transform, frequency domain, and time domain are transmuted and extracted via ML approach for classification and monitoring activity of the human. The application of DL to automated feature representation was projected to lessen the difficulty based on increased performance accuracy and handcrafted features.

Conventional cloud based frameworks for Big Data analyses are capable of providing better efficiency and consistency while assisting latency critical and non-safety IoT applications [11]. However, if the end-user is a person with time-sensitive and critical requirements, a huge amount of accessibility and robustness is needed, as the existence of disconnections from the central network or latency or bandwidth, variants might have a drastically negative effect and leads to serious impact on case of an emergency [12]. The increasing attention towards frameworks realizes the collaboration of Edge, Cloud, and Fog computing is recently developing. The major aim is to utilize the wider possibility of low level fog nodes and edge nodes for handling data processing, analyses, inference, correlation, and functional tasks [13]. This method represents a promising solution to the execution of reliable distributed healthcare services and applications, as a smart mapping of resource management and computation tasks through the nodes for meeting the essential needs of IoMT system. The research contribution of this work are as follows,

- A new hyper parameter optimized deep learning model for medical data classification in IoT enabled cloud environment, which allows the IoT devices to gather healthcare data and diagnose diseases in the cloud server.
- The IoT devices are employed for data acquisition and data preprocessing is carried out to improve the data quality.
- A convolutional neural network-long short term memory (CNN-BILSTM) technique is employed for classification purposes, which identifies the presence of diseases or not.
- For boosting the classification performance of the CNN-BILSTM model, a black widow optimization (BWO) approach is applied to compute the optimal learning rate of the CNN-BILSTM model.

Threats to authenticity can be divided into four groups, including those to premise validity, internal consistency, concept validity, and confirmability.

- Premise validity- Several potential causes that could result in incorrect results, such as erroneous associations between outcomes and predictor variables, are considered.
- Internal consistency - All potential factors (extraneous variables), that are not necessarily key predictors but may influence the outcome variable,
- Concept validity- If the measurements or indicators used in the investigation do not adequately depict the ideas they stand for
- Confirmability - It determines if the study's findings hold up in conditions that weren't considered in the actual study.

2. LITERATURE REVIEW

Kumar et al. [14] presented a novel IoT and Cloud based Mobile Healthcare applications for diagnosing and monitoring severe diseases. Now, a novel architecture is established for the people. Additionally, they proposed a novel classification approach called Fuzzy Rule based Neural Classifier to diagnose the severity and the disease. Praveen et al. [15] presented a novel OGSO based clustering using DNN named OGSO-DNN method for the shared healthcare schemes. The OGSO method was employed for selecting the CHs from the presented IoT device. The elected CH transmits the data to cloud server, i.e., later performs DNN based classification procedure for healthcare diagnoses.

Yu et al. [16] proposed a hybrid framework, named EdgeCNN, which balances the ability of edge computing and CC for addressing this problem for agile learning of health care data from the IoT device. This could considerably decrease the network I/O and learning latency, alleviate the pressure on cloud architecture for massive data and large user groups, and dramatically decreases the cost to maintain and build cloud frameworks. For verifying the possibility of EdgeCNN, they designed a group of streamlined diagnoses and learning methods for edge computing depends onCNN), facilitate EdgeCNN for identifying and inferring ECG in real world, since a particular healthcare application utilizing smart devices on the edge.

He et al. [17] proposed an effective cloud and edge model for maintaining ECG classification efficiency when decreasing the transmission cost. Such contribution includes: (i) present a hybrid smart medical framework called EdgeCNN which balances the ability of edge computing and CC for addressing the problem for agile learning of health care data from the IoT device. (ii) Introduce an efficient DL method for inferring ECG that could be placed for running on edge smart devices for lower latency diagnoses. (iii) Designed a data improvement technique for ECG on the basis of deep convolution generative adversarial network for expanding ECG data amount.

Juyal et al. [18] concentrated on improving the diagnosis procedure of skin diseases and connecting the gap among cure and diagnoses. This study presents a novel 'Intelligent' Skin Monitoring Device concept which permits patient in rural regions for monitoring skin disease remotely. The presented technique contains cloud based IoT and AI, in which CNN is utilized for analyzing the disease predictions and medical images. Veeramakali et al. [19] improve an optimum ODLSB enabled smart IoT and healthcare diagnoses method. The presented method includes medical diagnosis, secure transaction, and hash value encryption. The ODLSB method consists of OPSO method for sharing secret medical images. Moreover, the hash value encryption procedure preforms by NIS approach. Eventually, the ODNN is employed as a classification method for diagnosing the disease.

Liu et al. [20] proposed a smart dental health IoT scheme that depends on DL, mobile terminal, and smart hardware aims at examining the possibility of its application in in-home dental healthcare. Furthermore, smart dental devices are developed and designed in this work for performing image acquisition of teeth. Depending upon the dataset of twelve six hundred medical images gathered by the presented device from ten private dental hospitals, an automated diagnoses method trained with MASK R-CNN is established for the classification and detection of seven distinct dental diseases includes dental plaque, decayed tooth, periodontal, and uorosis disease, using the diagnoses accuracy of them reaches upto 90%, high specificity and high sensitivity.

Amin et al. [21] presented the stimulation result of an EEG pathology classification method that utilizes DL approach. They employed a range of healthcare smart sensors, includes an EEG smart sensor, to monitor and record multimodal healthcare data repeatedly. The EEG signals from patientsare transferred through smart IoT devices to the cloud, in which they are managed and transmitted to a cognitive model. The scheme defines the condition of the person by observing sensor analyses, like speech, facial expressions, gestures, EEG, and movements. Akhbarifar et al. [22] presented a remote health monitoring method that employs a lightweight block encryption technique to provide security for medical and health data in cloud based IoT platforms.

Even though a lot of improvements are addressed in Medical Data Classification, there still exist some challenges associated with the machine learning methods. The first challenge associated with machine learning was regarding the high-dimensional data that generated several tens of thousands of features for training the classifier. The second challenge was regarding the size of the publicly existing dataset with a fewer number of samples. The third challenge was regarding the presence of the unlabeled data. The labeled data accounts for just a fraction of the whole dataset and at the same time, these huge volumes of the unlabeled data consist of rich information for classifying cancers such that obtaining this information requires deeper extraction steps. These challenges make cancer classification a hectic task.

3. THE PROPOSED MODEL

The proposed method involves different processes such as data acquisition, preprocessing,

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classification, and hyper parameter optimization. The working process of the proposed model is demonstrated in Fig. 1. The overall process can be divided into three major stages. In stage-1, the collected medical data is preprocessed in different ways to enhance the data quality. Next, in stage-2, the CNN-BILSTM technique gets executed to classify the preprocessed medical data. Finally, in stage-3, the BWO algorithm is applied to determine the learning rate of the CNN-BILSTM model and thereby improves the classification performance.

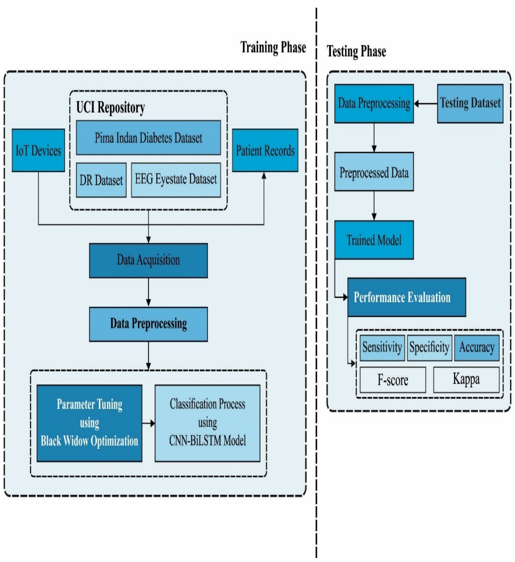

Figure 1: Block diagram of the proposed model

3.1 Stage 1: Data Pre-processing

In this stage, the IoT device initially capture the medical data of the patients and are pre-processed. At the time of data pre-processing, the input data in any format are transformed into the .arff format for making it compatible to more processing. Followed by, the resultant pre-processing data endure classification with utilize of new CNN-BILSTM model.

3.2 Stage 2: Data Classification

During data classification process, the preprocessed data is fed as input to the CNN-BILSTM model to determine the proper class labels.The CNN has the characteristics of focusing more interest on the apparent features in the sightline, hence it is broadly utilized in feature engineering. It can be characteristics of increasing based on the series of time, and it can be broadly utilized in time sequence. Based on the features of LSTM and CNN, a stock predicting method depends on CNN-LSTM is developed. The major structures of LSTM & CNN, include full connection layer, pooling layer, input layer, 1D convolutional layer, and LSTM hidden layer.

It is a type of FFNN that has better performances in natural language processing and image processing. It could be efficiently employed to the predicting of time sequences. The weight sharing and local perception of CNN could highly decrease the amount of variables, therefore improving the performance of learning module [23]. CNN is generally made up: pooling and convolutional layers. Every convolutional layer comprises a large number of convolutional kernels, and its calculated equation is displayed in Eq. (1). Afterward, the convolutional process of the convolutional layer, the feature of data is removed, but, the removed feature dimension is higher, hence to resolve this issue and decrease the cost of network trained, a pooling layer is included afterward the convolutional layer for reducing the dimension feature:

$$l_t = \tanh(x_t * k_t + b_t), \qquad \text{--- (1)}$$

Whereas l_t denotes the output value afterward convolutions, tanh indicates the activation function, x_t represents the input vector, k_t signifies the weight of convolutional kernel, and b_t denotes the bias of convolutional kernel.

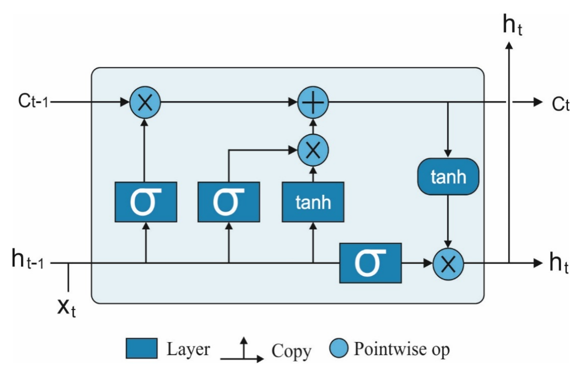

Figure 2: Framework of LSTM model

It is proposed for solving the longstanding problem of gradient disappearance and explosions in RNN. It is broadly utilized in emotional analysis, text analysis, and speech recognition since it contains its individual storage and could create precise predictions. Recently, it was adapted in the area of stock market predicting. It has one repeating method in a regular RNN and simple internal framework. It is generally a tanh layer. But, the 4 LSTM models are equivalent to the regular RNN models, and they function in a unique interactive

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way. The LSTM memory cell comprises: output gate, forget gate, and input gate as displayed in Fig 2.

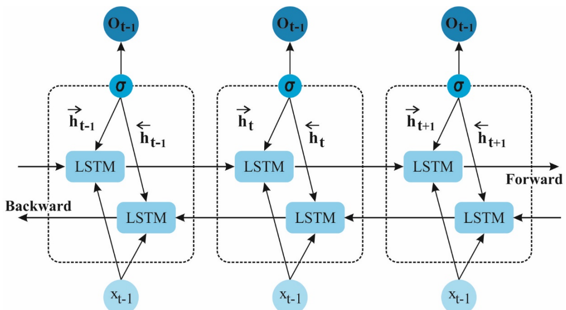

Figure 3: Architecture of Bi-LSTM model

The framework of BiLSTM module was given by Fig. 4. Consider the input of time t is w_t, in time t-1, therefore the outcome of forward hidden unit is $\vec{h}$, and simulation result of the backward hidden unit is $\overleftarrow{h}_{(t+1)}$, Finally, the attained results of backward and hidden in at time tis given in the following:

$$\vec{h}_t=L(w_t,\vec{h}_{(t-1)},c_{(t-1)}) \quad (2)$$

$$\overleftarrow{h}_t=L(w_t,\overleftarrow{h}_{(t+1)},c_{(t+1)}) \quad (3)$$

where L (·) denotes hidden layer task of LSTM hidden layer. The forward output vector is $\vec{h}_t \in R^{(1\times H)}$ where the backward output vector is $\overleftarrow{h}_t \in \leftarrow R^{(1\times H)}$, and this vector should be combined for getting the text feature. It is obvious that H denotes amount of hidden layer cells:

$$H_t=\vec{h}_t \parallel \overleftarrow{h}_t\leftarrow \quad (4)$$

The procedure of prediction and training is displayed below.

i. Input data: Provide the data needed for CNN-BiLSTM training.

ii. Data regularization: since it has a maximum gap in the input data, for training the module well, the z- score regularization technique is adapted to regularize the input data, as follows:

$$y_i=(x_i-\bar{x})/s, \quad (5)$$

$$x_i=y_i*s+X, \quad (6)$$

in which y_i denotes the regularized value, x_i indicates the input data, X represents the average of input data, and s signifies the SD of input data.

iii. Initialize network: initialization the bias & weight of all the layers of CNN-LSTM.

iv. CNN layer estimation: the input data is consecutively passed by the pooling and convolutional layers in the CNN layer.

v. LSTM layer estimation: The outcome of the CNN layer is estimated by the LSTM layer, and the outcome value is attained.

vi. Outcome layer estimation: the outcome value of LSTM layer is inputted to the fully connected layer for getting the outcome value.

vii. Estimation error: the outcome value estimated through the outcome layer is related to the real value of this set of data, and the equivalent errors are attained.

viii. For judging either the termination criteria are fulfilled: the condition for the termination is to finish a predefined amount of cycles, the weights are lesser compared to particular threshold, and the error rates of predicting are lesser compared to particular threshold. When every condition for the termination is encountered, the training would be finished, then upgrade the whole CNN-LSTM network, and proceed to step 10; or else, proceed to step 9.

ix. Error BP: transmit the estimated error in the direction-way, upgrade the weights and biases of all the layers, and proceed to step 4 to proceed for training the network.

x. Store the module: store the trained module for predicting.

xi. Input data: Feed the data needed for the predicting.

xii. Data regularization: the input data are regularized.

xiii. Predicting: input the regularized data to the trained module of CNN-LSTM, and later attain the equivalent outcome value.

xiv. Data regularized return: the outcome value attained by the module of CNN-LSTM is the regularized value, and the regularized value is returned to the original value. As displayed in Eq. (9). Whereas x_i denotes the regularized returned value, y_i denotes the outcome value of CNN-LSTM, s indicates the SD of input data, and X represents the mean value of input data.

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xv. Outcome results: Display the returned outcomes for completing the predicting procedure.

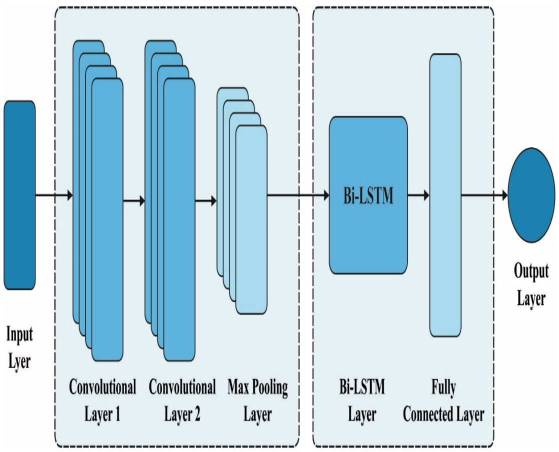

Figure 4: Structure of CNN-BiLSTM model

3.3 Stage 3: Learning Rate Scheduling Process

For improving the classification performance of the CNN-BILSTM model, the BWO algorithm is employed to compute the optimal learning rate in such a way that the overall classification performance is raised to the next level.The BWO was reproducing the lifespan of development of the black widow spider (BWS). In general, female BWSs create the net in the night and authorization few pheromones in anywhere of her net for attracting male black spiders for having mate. The male BWS obtain involved as this pheromone and link in the net. The female BWS feeds the male BWS afterward or in mate. Next mate, the female black widow places egg sock on net. Other young spiders from net are regarded as the fittest young spider dependent upon this model; this BWO was established [24].The BWO algorithm continues with arbitrary primary BWS population. This population is male as well as female BWS to create offspring for next generation. A primary population of BWS is written as:

$$X_{N,d} = \begin{bmatrix} x_{1,2} & x_{1,2} & x_{1,3} & \cdots & x_{1,d} \\ & & \vdots & & \\ x_{N,1} & x_{N,2} & x_{N,3} & \cdots & x_{N,d} \\ & lb \le X_i \le ub & & & \end{bmatrix} \quad (7)$$

where X_d implies the population of BWS, d represents the amount of decision variable, N refers the amount of populations, lb stands for the lower bound of populations, and ub indicates the upper bound of populations. The potential solution population ($X_{(N,d)}$) are utilized for minimizing or maximizing the subsequent objective functions signifies in Eq. (8):Subsub section has to be in sentense case with no spacing above or blow the srat of it.

$$Objective\ function = f(X_{N,d}) \quad (8)$$

The next procedure in BWO is replicating the young spider from male as well as female spider's mating. During or after mate, male spider is eaten by female spider. The arbitrary election procedure was utilized for selecting the pair of spiders to mate for reproducing young spiders. The reproduction model of BWO is written as formula provided as Eq. (9):

$$Y_{i,d} = \beta \times X_{i,d} + (1-\beta) \times X_{j,d}$$
$$Y_{j,d} = \beta \times X_{j,d} + (1-\beta) \times X_{i,d} \quad (9)$$

where Y_(i,d), and Y_(j,d) are the young spider from reproductions, i and j are an arbitrary number amongst 1 to N and β represent the arbitrary number among [0-1]. For avoiding arbitrary duplication election of pairs, the reproduce model is performed for d/2 times.

Afterward, reproduce, the mother and young spider populations are arranged with its Fitness Function (FF) value and cannibalism rate (CR). The next procedure in the BWO is mutation. The young spider is elected dependent upon the mutation rate, and a lesser arbitrary values are additional with elected young spider for mutation, and this procedure was written as Eq. (10):

$$Z_{k,d} = Y_{k,d} + \alpha \quad (10)$$

whereZ_d implies the mutated spider populations, Y_d represents the arbitrarily elected young spider, k stands for the arbitrary number, and α signifies the arbitrary mutate values.This BWO algorithm is dependent upon 3 parameters such as the reproduction rate (RR), CR, and mutation rate (MR). The RR control the generation of young spider and gives chances for exploring the search space to find optimum solutions. The CR control the weak fittest populations in the generation, and only the strong fittest population is permitted to the next generation. The MR control the variety in current to next generations.

4. PERFORMANCE VALIDATION

The presented technique is simulated utilizing Python 3.6.5 tool. The results are examined on three different dataset namely PIMA Indians diabetes dataset, DR Dataset, and EEG EyeState dataset. The details related to the dataset is provided in Table 1.

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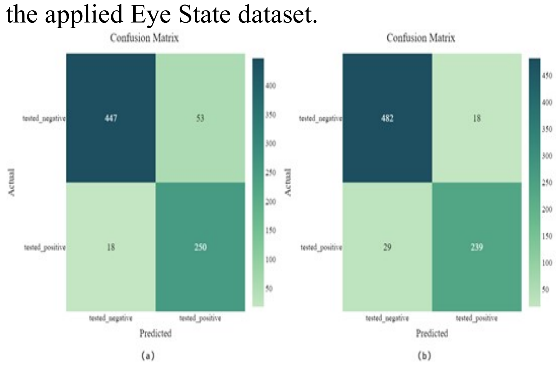
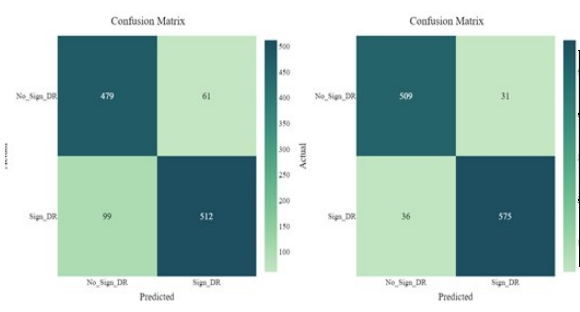
TABLE 1: DATA SET DESCRIPTION

Description	Pima Indian Diabetes	Diabetic Retinopathy	EEG Eye State
No. of Instances	768	1151	7849
No. of Attributes	8	19	14
No. of Class	2	2	2
% of Positive Samples	34.90%	53.08	62.21
% of Negative Samples	65.10%	46.92	37.79
Data sources	[25]	[26]	[27]

Fig. 5 depicts the set of confusion matrices generated by the presented technique on the applied dataset. Figs. 5a-b depicts the confusion matrices obtained by the presented approach on the applied PIMA Indians diabetes dataset. Similarly, the Figs. 5c-d showcases the confusion matrices gained by the presented approach on the applied DR dataset. Likewise, the Figs. 5e-fillustrates the confusion matrices attained by the presented methodology on the applied Eye State dataset.





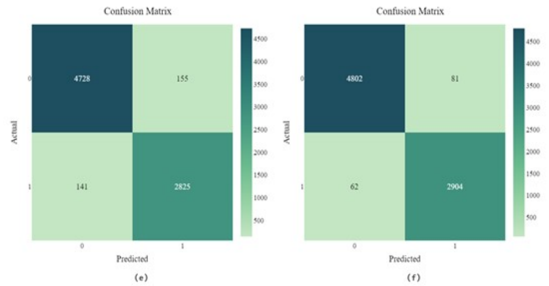


Figure 5: Confusion Matrix (a-b) Pima Indian Diabetes Dataset (c-d) Diabetic Retinopathy Dataset (e-f) EyeState Dataset

4.1 Results Analysis on PIMA Indians Diabetes Dataset

Table 2 and Fig. 6 investigates the classification results analysis of the BWO-CNN-BiLSTM technique with the CNN-BiLSTM technique on the applied PIMA Indians Diabetes dataset. The experimental outcomes have shown that the BWO-CNN-BiLSTM technique has obtained a higher accuracy of 93.88% whereas the CNN-BiLSTM technique has depicted a lower accuracy of 90.76%. It is also observed that proposed BWO-CNN-BiLSTM model has obtained slightly reduced specificity compared to the CNN-BiLSTM model due to the fact that the BWO-CNN-BiLSTM model has classified 239 instances into positive class label whereas the CNN-BiLSTM model has classified 250 instances into positive class label. However, the BWO-CNN-BiLSTM model has resulted to higher accuracy of 93.88%, which is higher than the accuracy obtained by the other methods. From these values, it is demonstrated that the BWO-CNN-BiLSTM technique has accomplished improved performance due to the parameter tuning using BWO algorithm.

TABLE 2: RESULT ANALYSIS OF EXISTING WITH PROPOSED BWO-CNN-BILSTM METHOD FOR PIMA INDIAN DIABETES DATASET

Methods	Sensitivity	Specificity	Accuracy	F-score	Kappa
BWO-CNN-BiLSTM	96.40	89.18	93.88	95.35	86.40
CNN-BiLSTM	89.40	93.28	90.76	92.64	80.25

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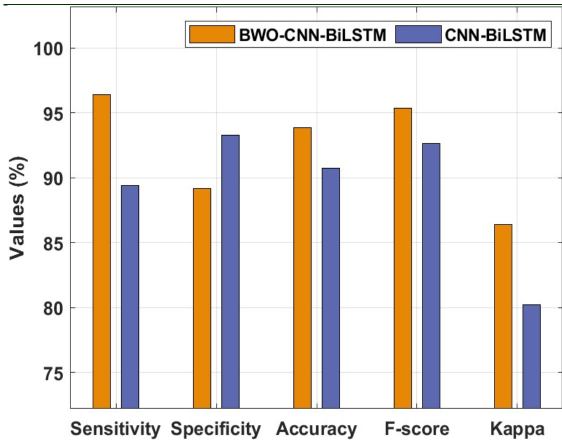

Figure 6: Result analysis of BWO-CNN-BiLSTM Method on Pima Indian Diabetes Dataset

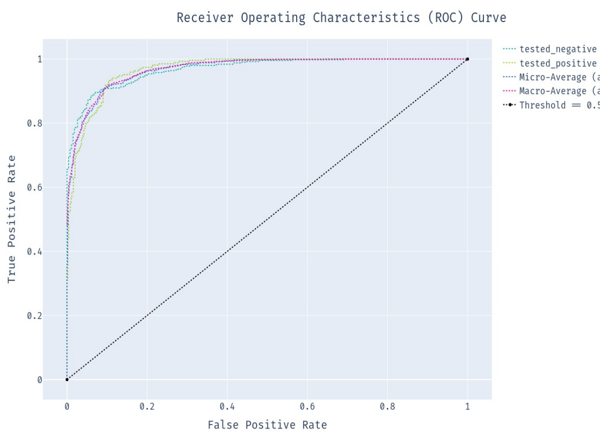

Figure 7 : ROC analysis of CNN-BiLSTM model on PIMA Indians Diabetes dataset

Fig. 7 illustrates the ROC curve analysis of the CNN-BiLSTM technique on the applied PIMA Indians diabetes dataset. The figure depicted that the CNN-BiLSTM technique has demonstrated maximum outcome with a higher ROC of 0.97.

Fig. 8 exemplifies the ROC curve examination of the BWO-CNN-BiLSTM technique on the applied PIMA Indians diabetes dataset. The figure portrayed that the BWO-CNN-BiLSTM technique has revealed better performance with a higher ROC of 0.99.

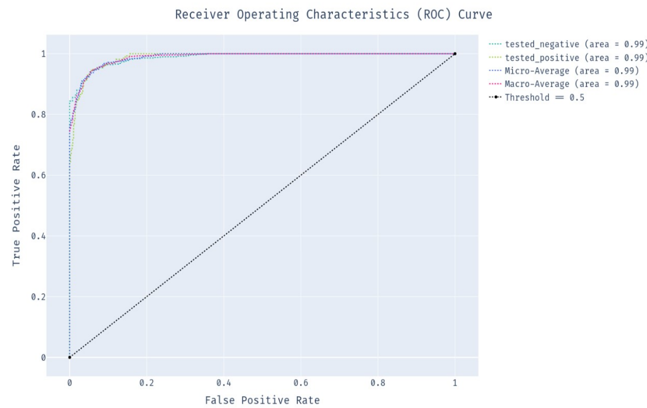

Figure 8: ROC analysis of BWO-CNN-BiLSTM model on PIMA Indians Diabetes dataset

A detailed comparison study of the BWO-CNN-BiLSTM technique with existing techniques takes place on the PIMA Indians Diabetes dataset in Table 3 and Fig. 9. The experimental outcomes highlighted that the Rotation Forest and TLBO+RBFN techniques have accomplished inferior outcomes with the least accuracy of 67.20% and 66.66% respectively. Followed by, the iTLBO+RBFN and ROF+KELM techniques have gained slightly improved performance with the accuracy of 81.77% and 78.91% respectively. However, the BWO-CNN-BiLSTM technique has resulted in a maximum accuracy of 93.88%.

TABLE 3: COMPARATIVE WITH RECENT TECHNIQUES WITH RESPECT TO ACCURACY FOR DIABETES DATASET

References	Classifiers	Accuracy (%)
Proposed	BWO-CNN-BiLSTM	93.88
Dash et al., 2019 [28]	TLBO+RBFN	66.66
Dash et al., 2019 [28]	iTLBO+RBFN	81.77
Lv and Han, 2018 [29]	Rotation Forest	67.20
Lv and Han, 2018 [29]	ROF+KELM	78.91

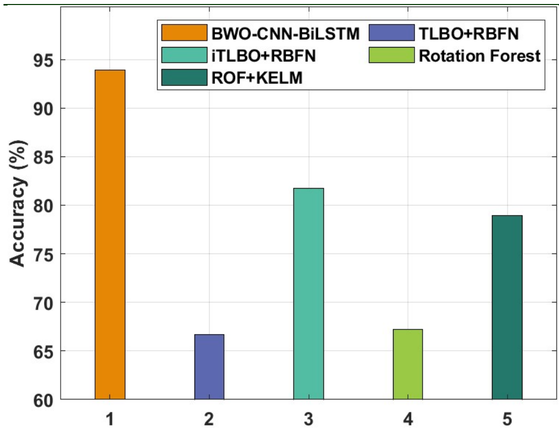

Figure 9 : Accuracy analysis of BWO-CNN-BiLSTM model on PIMA Indians Diabetes dataset

4.2 Results Analysis on Diabetic Retinopathy Dataset

Table 4 and Fig. 10 explores the classification outcomes analysis of the BWO-CNN-BiLSTM approach with the CNN-BiLSTM method on the applied DR Dataset. The experimental outcomes outperformed that the BWO-CNN-BiLSTM technique has achieved an increased accuracy of 94.18% whereas the CNN-BiLSTM algorithm has showcased a minimum accuracy of 85.69%. From these values, it can be showcased that the BWO-CNN-BiLSTM methodology has accomplished higher efficiency because of the parameter tuning utilizing BWO technique**.**

TABLE 4: RESULT ANALYSIS OF EXISTING WITH PROPOSED BWO-CNN-BILSTM METHOD FOR DIABETIC RETINOPATHY DATASET

Methods	Sensitivity	Specificity	Accuracy	F-score	Kappa
BWO-CNN-BiLSTM	94.26	94.11	94.18	93.82	88.32
CNN-BiLSTM	88.70	83.80	86.10	85.69	72.21

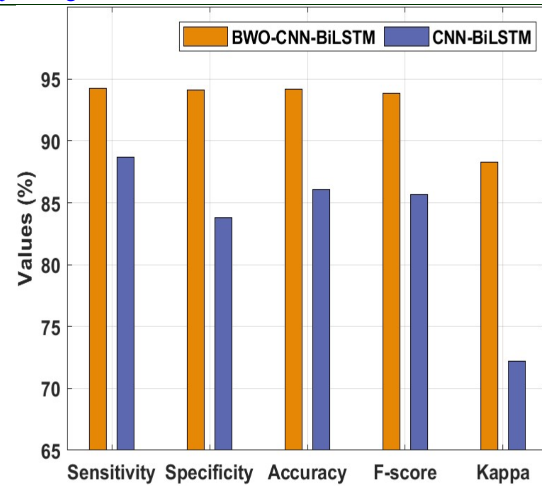

Figure 10 : Result analysis of BWO-CNN-BiLSTM Method on DR Dataset

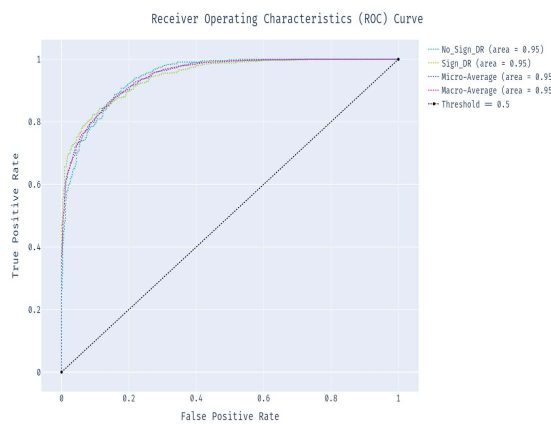

Figure 11 : ROC analysis of CNN-BiLSTM method on DR Dataset

Fig. 11 demonstrates the ROC curve analysis of the CNN-BiLSTM manner on the applied DR Dataset. The figure outperformed that the CNN-BiLSTM algorithm has exhibited maximal results with superior ROC of 0.95.

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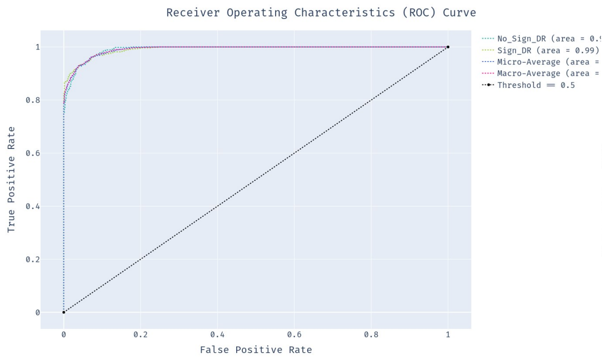

Figure 12 : ROC analysis of BWO-CNN-BiLSTM on DR Dataset

Fig. 12 demonstrates the ROC curve examination of the BWO-CNN-BiLSTM algorithm on the applied DR Dataset. The figure showcased that the BWO-CNN-BiLSTM manner has exposed better efficiency with a maximum ROC of 0.99.

A brief comparison analysis of the BWO-CNN-BiLSTM algorithm with existing approaches takes place on the DR Dataset in Table 5 and Fig. 13. The experimental outcomes outperformed that the NB+PCA+Firefly and KNN+PCA+Firefly methods have accomplished inferior outcomes with the worse accuracy of 70.20% and 72.30% respectively. At the same time, the SVM+RF and SVM+PCA+Firefly approaches have attained slightly superior performance with the accuracy of 75% and 76% respectively. Moreover, the PSO+N and XGBoost-PCA techniques have outperformed moderate results with accuracy of 76.11% and 80% respectively. Eventually, the BWO-CNN-BiLSTM methodology has resulted in a maximal accuracy of 94.18%.

TABLE 5: RESULT COMPARISON WITH PRIOR WORK

References	Classifiers	Accuracy (%)
Proposed	BWO-CNN-BiLSTM	94.18
Gadekallu et al., 2020 [30]	XGBoost-PCA	80.00
Gadekallu et al., 2020 [30]	NB+PCA+Firefly	70.20
Gadekallu et al., 2020 [30]	KNN+PCA+Firefly	72.30
Gadekallu et al., 2020 [30]	SVM+PCA+Firefly	76.00
Elnahas et al., 2019 [31]	SVM+RF	75.00
Herliana et al., 2018 [32]	PSO+NN	76.11

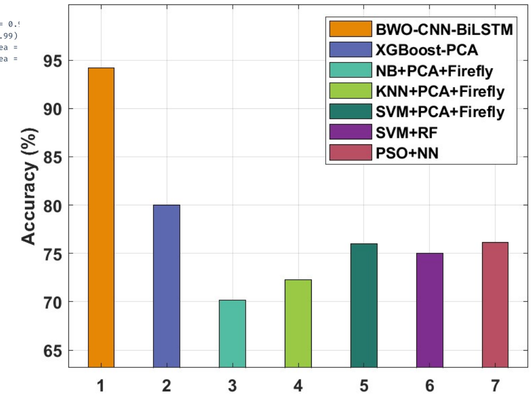

Figure 13 : Accuracy analysis of BWO-CNN-BiLSTM model on DR Dataset

4.3 Results Analysis on EEG EyeState Dataset

Table 6 and Fig. 14 examine the classification outcomes analysis of the BWO-CNN-BiLSTM approach with the CNN-BiLSTM manner on the applied EEG EyeState dataset. The experimental outcomes displayed that the BWO-CNN-BiLSTM method has gained an increased accuracy of 98.18% whereas the CNN-BiLSTM technique has outperformed a minimal accuracy of 96.23%. From these values, it can be depicted that the BWO-CNN-BiLSTM method has accomplished increased efficiency because of the parameter tuning utilizing BWO technique.

TABLE 6: RESULT ANALYSIS OF EXISTING WITH PROPOSED BWO-CNN-BILSTM METHOD FOR EEG EYESTATE

Methods	Sensitivity	Specificity	Accuracy	F-score	Kappa
BWO-CNN-BiLSTM	98.34	97.91	98.18	98.53	96.13
CNN-BiLSTM	96.83	95.25	96.23	96.96	91.99

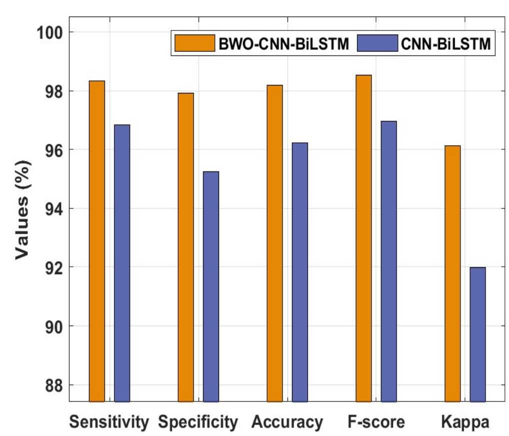

Figure 14 : Result analysis of BWO-CNN-BiLSTM Method on EEG EyeState Dataset

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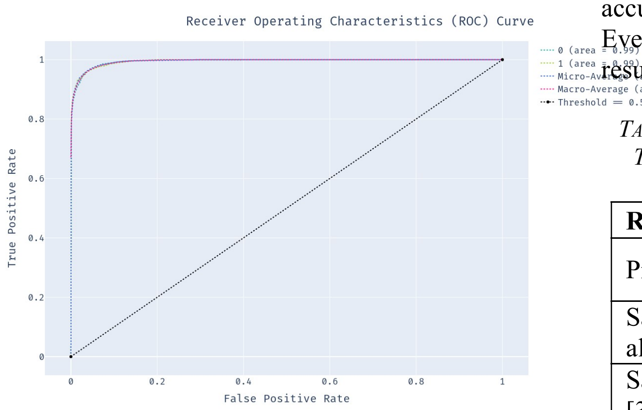

Figure 15 : ROC analysis of BWO-CNN-BiLSTM model on EEG EyeState Dataset

Fig. 15 shows the ROC curve analysis of the CNN-BiLSTM algorithm on the applied EEG EyeState Dataset. The figure demonstrated that the CNN-BiLSTM manner has outperformed higher results with superior ROC of 0.99.

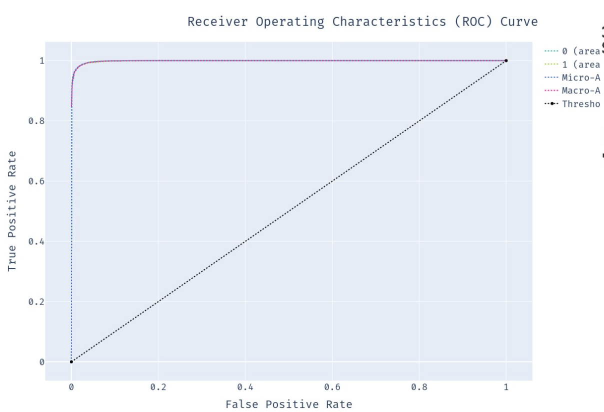

Figure 16 : ROC analysis of CNN-BiLSTM model on EEG EyeState Dataset

Fig. 16 represents the ROC curve examination of the BWO-CNN-BiLSTM approach on the applied EEG Eye State Dataset. The figure outperformed that the BWO-CNN-BiLSTM manner has exposed optimum efficiency with superior ROC of 1.00.

A comprehensive comparative analysis of the BWO-CNN-BiLSTM method with existing algorithms takes place on the EEG Eye State Dataset in Table 7 and Fig. 17. The experimental outcomes highlighted that the IAL-TSC and SA+LSTM manners have accomplished inferior results with the worse accuracy of 72.60% and 84.49% correspondingly. Likewise, the Cosine+KNN and RBF+IPSO methodologies have attained somewhat increased efficiency with the accuracy of 93.50% and 95.19% correspondingly. Eventually, the BWO-CNN-BiLSTM algorithm has resulted in a maximal accuracy of 98.18%.

Table 7: Result Analysis of Existing with Proposed TLBO-KELM Method for EEG EyeState Dataset

References	Methods	Accuracy
Proposed	BWO-CNN-BiLSTM	98.18
Sathyabama et al., [33]	SA+LSTM	84.49
Satapathy et al., [34]	RBF+IPSO	95.19
Yilmaz et al., [35]	Cosine+KNN	93.50
Wang et al., [36]	IAL-TSC	72.60

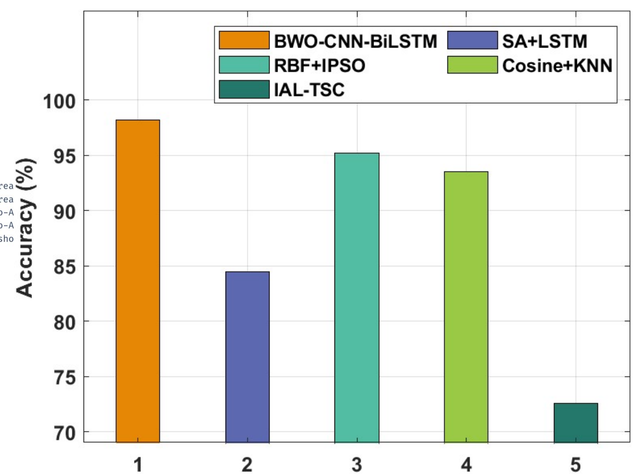

Figure 17: Accuracy analysis of BWO-CNN-BiLSTM model on EEG EyeState Dataset

By looking into the aforementioned tables and figures, it can bestated that the BWO-CNN-BiLSTMapproach has been found to be an appropriate tool for medical data classification in the IoT and cloud environment

5. CONCLUSION

In this study, a new DL based medical data classification model is developed to assist diagnostic processes in the IoT and cloud environment. The proposed model has the ability to properly identify the presence of diseases using the medical data gathered by the IoT devices. The proposed model performs data preprocessing at the initial stage to improve the quality of data and make it compatible with classification process. Moreover,

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the design of CNN-BILSTM model helps to classify the preprocessed healthcare data and thereby effectually allot proper class labels to them. Finally, a learning rate scheduler using BWO algorithm is designed to optimally elect the learning rate of the CNN-BILSTM model. The utilization of the BWO technique for the optimum selection of learning rate considerably boosts the classification performance to a maximum extent. A comprehensive set of simulations are performed on benchmark dataset and examined the outcomes interms of different measures. The experimental results showcased the significant performance of the proposed model over the recent state of art techniques. The advantage of work is, it provides flexibility, less over fitting and provides extensive support with missing data. The limitations are run slowly, lack of transparence to results. In future, the proposed model is extended to the design of feature subset selection and outlier detection techniques. Redundancy, Outliers affects the Classifier's Classification performance. We want to find different ways to remove the outliers, duplicate data from the Pima Indian Diabetes Dataset. It may help to increase the classification accuracies of the deep learning method.

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