Adaptive Ensembled Fusion Based Deep CNN-Bilstm Model For Heart Disease Prediction In IoT

Priyanka Dhaka*[1], Ruchi Sehrawat[2]

[1] Research Scholar Guru Gobind Singh Indraprastha University and Assistant Professor, MaharajaSurajmal Institute, GGSIPU, Delhi, India
[2]University School of Information and Communication Technology, GGSIPU, Delhi, India
Emails: priyankadhaka@msijanakpuri.com; ruchi.sehrawat@ipu.ac.in

Abstract

Internet-of-Things (IoT)-based heart disease prediction is a complex task and processing the real collected data directly for remote patient monitoring suffers from the limitations due to the irrelevant data features, affecting the prediction accuracy and raising the security concerns. Hence, the efficient Adaptive ensembled deep Convolution neural network –Bidirectional Long Short Term Memory (Adaptive ensembled deep CNN-BiLSTM) classifier model is proposed via the fusion of interactive hunt-based CNN and Whale on Marine optimization (WoM)-based deep BiLSTM. The Adaptive optimization developed from the standard hybrid characteristics such as random searching, seeking, attack prohibition, following, and waiting characteristics optimized the fusion parameters of the developed classifier for attaining high detection accuracy. Additionally, the modified Elliptic Curve Cryptography (ECC) based Diffi-Huffman encryption algorithm provides the authentication and security of sensitive patient data in heart disease prediction. The developed model is evaluated with other competent methods in terms of accuracy, sensitivity, specificity as well as F-measure, which are reported as 97.573%, 98.012%, 97.592%, and 97.705% respectively.

Keywords: IoT; Smart healthcare monitoring; Elliptic Curve Cryptography; Convolution neural network; Diffi-Huffman encryption algorithm; Synthetic Minority Over-sampling Technique (SMOTE); Deep learning (DL).

1. Introduction

Cardiovascular disease refers to a variety of conditions, including rheumatic, coronary, and congenital heart disease. As a result, the heart's activity has been studied when exercising, sleeping, and working [1] [2]. Chest pain, uneasiness, shortness of breath, perspiration, dizziness, and fatigue are all indications of heart disease [3]. Heart disease is the major cause of mortality across different age groups in the modern world, which insists on the need to better predict heart diseases using various innovative approaches [4]. Heart disease diagnosis is mostly based on existing knowledge and data from associated pathological occurrences [5].

Healthcare sectors rapidly adopted the IoT techniques [11] [12] as incorporating the IoT characteristics into medical devices enhances both the quality and efficacy of services. Smart wearable devices collect information about the patient's health state including their heart rate, blood pressure, glucose level, and so on. The collected data can be delivered to cell phones and continuously tracked using sensors on wearable technology [13][14]. The approaches integrate IoT into complicated deep learning(DL)models with the ultimate goal of attaining higher accuracy outcomes since it has an incredibly advantageous state of decreasing response time[15-18].DL models, like CNN, LSTM, ensemble classifiers, and so on are employed for heart disease prediction. DL algorithms handle enormous amounts of data and are crucial to the decision-making process. The more complex the network, the greater the prediction time, and the higher the accuracy acquired from the network[29]. The significant issue for IoT applications in the healthcare and other domains is the requirement of real-time data for the operation [26].

The research focuses on developing an effective heart disease prediction framework utilizing the Adaptive ensembled deep CNN-BilSTM model. The Diffi-Huffman encryption scheme based on modified ECC

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

authenticated the patient data and ensured the data security. To enhance model performance and address the issue of data imbalance, the method adopts the SMOTE oversampling approach that produces synthetic samples [27]. Finally, the Adaptive ensembled deep CNN-BilSTM model performed the classification for disease prediction.

- **Adaptive optimization:** The hybrid swarm is inspired by the seeking, swarming, chasing, and foraging characteristics that offer multiple merits including good robustness, the ability to perform global searches, tolerance for parameter settings, and the capacity to be insensitive to initial values. Additionally, the adaptive optimization offered a balance between the exploration and exploitation stages for fixed-dimension problems.
- **Adaptive ensembled deep CNN-BilSTM classifier:** The Adaptive ensembled deep CNN-BilSTM model is formed by the fusion of interactive hunt-based CNN and WoM-based deep BiLSTM. Additionally, the adaptive optimization optimized the fusion parameters of the Adaptive ensembled deep CNN-BilSTM model and classified the sequential data for predicting heart disease.

The entire research is organized as follows: Section 2 comprises the overview of the existing techniques relevant to heart disease prediction in IoT, and Sections 3 and 4 provide an overview of the research's methodology and implementation analysis. Finally, Section 5 concludes the outcome of the developed research.

2. Literature review

This section comprises a review of the existing techniques to support the researchers in making significant contributions. Yuanyuan Pan et al. [3]developed a CNN model for predicting Heart Disease with IoT assistance in which the deep multi-layer perception was utilized to build the prediction model. The method was secured with linear regularization and nonlinear functions using sigmoid classification specialized learning technologies. Additionally, the model provided extremely accurate and trustworthy heart disease diagnoses and eliminated misdiagnoses. Further, the accuracy can be aided by including the feature selection approaches. The future work includes the integration of advanced Artificial Intelligence (AI) to further increase precision.

Mohammad Ayoub Khan et al. [14] contributed a wearable IoT-enabled heart disease prediction framework employing altered CNN that addressed the problem of low accuracy. The heart monitor device and smartwatch are affixed with the patients that continuously track their blood pressure and electrocardiogram (ECG). The obtained sensor data was further classified into normal and pathological utilizing the modified CNN classification. The cuttlefish optimization was employed to select the features that enhanced the accuracy. Further other advanced feature selection approaches can be employed in the future.

Parag Verma et al. [18] integrated the DL technique into edge IoT devices that addressed latency issues. However, as opposed to utilizing the average, the majority voting basis counts were utilized for the outcomes of the probability calculations. The efficacy of the framework was accessed in terms of network throughput, latency, jitter, and so on. Further different training models can be employed to boost accuracy and performance can be assessed by extending the method to different medical fields including cancer and diabetes, as well as hepatitis for effective assistance.

Simanta Shekhar Sarmah et al. [25] utilized an IoT-enabled modified Neural Network(NN) for detecting heart disease that addressed security issues. The authentication process was utilized to confirm the patients of the specific hospital. Further, the wearable IoT sensor gadget was fixed to the patient, and sensor data was transmitted to the cloud. Finally, the advanced encryption safely encrypted the sensor data and the classification was exhibited utilizing the modified NN. The method offered high security and lowest time for encryption as well as decryption.

Shreshth Tuliet et al. [26] presented an IoT-enabled deep ensemble model for automatic disease detection. The method enabled the integration of complicated DL networks into edge computing paradigms with a unique communication and model distribution approach of the ensemble with high accuracy and offered low latency. Additionally, the training verified real-world heart patient data analysis on well-known datasets for real-time prediction. Further, the method can be applied to other domains of healthcare.

For the cardiovascular disease diagnosis Pati A. et al., [29] utilized a Fog framework with the DL prediction model the prediction model along with the fog node makes the model away from the attack but that may create congestion when the data flow increases.

For heart disease detection Nadeem M.W et al. [24] used the fusion-based SVM model where the fuzzzy-based decision makes the model attain high accuracy. However, this model requires a large amount of test data for validation.

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

2.1 Challenges

- The irrelevant features in the data affected the precision and generated errors during the classification. Hence appropriate feature selection techniques can be employed to boost the prediction [3].
- The model testing utilizing the sensor values acquired directly from IoT takes more time to predict the disease, and there is a high possibility of acquiring misdiagnosed results [14].
- The model requires a different preparation system at each worker node and is consolidated with aggregated stowing for improving efficiency increasing the complexity of the model [18].
- The method utilizing the ensemble classification requires sending the data to all worker nodes in the ensemble case, and the bandwidth utilization was found to be high and requires improvement. Highly advanced ensemble models can be employed in the future to enhance the accuracy [26].
- In the Multimodal IoT, the performance of disease prediction is limited due to bias and privacy issues. Additionally, the different heterogeneous data affected the efficiency of the model [28].

Many of the existing models struggled with precision due to the lack of a feature selection technique. This limitation justifies the need for the proposed method, which utilizes an Adaptive ensembled deep CNN-BiLSTM. This approach can potentially address the accuracy issue by integrating ensemble methods and deep learning techniques, which may inherently handle feature selection more effectively. Some models, especially those relying solely on deep CNN, required substantial training time to predict diseases accurately. The proposed method can be justified by its potential to address this challenge by incorporating an ensemble of deep CNN and BiLSTM, which may lead to faster and more accurate predictions. The DL approach used required a high cost for designing disease prediction frameworks with IoT. The proposed method can provide a cost-effective solution, as it leverages existing techniques but optimizes them through ensemble learning, potentially reducing the cost associated with the model's development. Security issues were highlighted in the use of sensitive patient data in IoT platforms. The proposed method emphasizes security and privacy through the use of an encryption algorithm and patient authentication. These measures can protect patient data and ensure compliance with privacy regulations. The proposed method addresses the data imbalance problem by incorporating the SMOTE. This technique generates synthetic samples of minority class instances, which can help balance the dataset.

3. Adaptive ensembled deep CNN-BilSTM classifier for IoT enabled Heart disease prediction

Most of the heart disease prediction framework utilizing the DL and IoT is found with several drawbacks. The DL-assisted CNN resulted in less precision due to the lack of a feature selection technique that affected the accuracy of the model. However, the modified deep CNN method requires more training time to predict the disease when using IoT sensor values directly and there is a chance that the results are inaccurate [14]. Furthermore, the DL approach required a high cost for designing the disease prediction framework with IoT [18]. Additionally, security issues are formed with the utilization of sensitive patient data in the IoT platform. Hence, the proposed method overcame the above-mentioned limitations using the hybrid optimized Deep CNN-BiLSTM with the encryption algorithm that predicted heart disease accurately and safely.

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

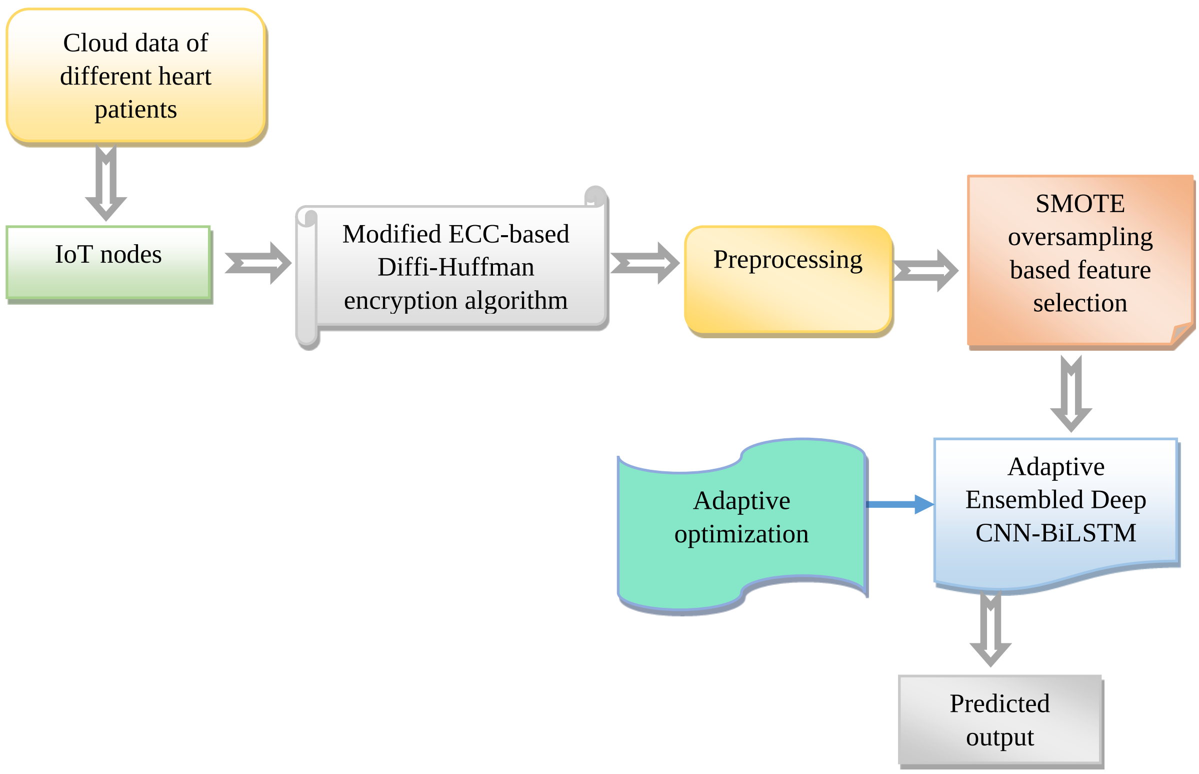


Figure 1: Block diagram for the Adaptive ensembled deep CNN-BilSTM framework for heart disease prediction in IoT

The proposed methodology utilizes an Adaptive ensembled deep CNN-BilSTM for heart disease prediction in IoT, which is schematically represented in Figure 1. The proposed model involves three phases, such as data collection via distributed IoT nodes, device, and patient authentication utilizing a Diffi-Huffman encryption based on modified ECC, and prediction utilizing an ensemble adaptive deep CNN-BiLSTM model. For health status prediction, IoT nodes are deployed in the sensing environment for initially gathering the data relevant to patients. The data is gathered and protected in the cloud utilizing encryption-based data security to inhibit illegal access. The SMOTE technique generates synthetic samples of minority class instances to improve model performance and minimize the bias to solve the data imbalance problem. The processed data is fed to an adaptive ensembled deep CNN-BilSTM classifier for predicting the disease.

3.1 Data collection utilizing IoT nodes

Before updating securely on a cloud server, the authentication process assures the verification and validity of the data. Hence, both the previously published and current medical reports are encrypted utilizing an ECC-based cryptographic method, which is uploaded to the cloud storage. Further, the encrypted files are decrypted and downloaded by the authorized user for further processing for disease prediction.

3.1. Input

The input data of the research is acquired from the datasets (DS)[19] and [20]are fed to the model and have the dimensionality of $[n \times 13]$,$[n \times 11]$ respectively, where n indicates the number of patients. Finally, the set of data collected from the databases $I = \{x_1, x_2, x_3, \ldots x_m\}$ is fed as the input to the disease prediction model.

3.1.2 Modified ECC-based Diffi-Huffman encryption and decryption: The method utilizes the modified Diffi-Huffman encryption method for data protection. The algorithm utilizes both the sender's private key and the recipient's public key for protecting the data in the cloud[21], and the authorized user holds the right to access the data from their respective hospital portals.

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

3.2 Preprocessing

Preprocessing enhances the quality of data in which tabular data contains the missing values of specific attributes related to the patients that may cause an error in the classification. Hence, the rows containing missing values are dropped for easing the classification. The data contains a different range of values for the multiple attributes. The data normalization is performed to normalize the different ranges to obtain an efficient classification. In data normalization, all data instances x are fixed to have a mean (μ_x) and a standard deviation (δ). Hence, the process reduces the dynamic ranges across the data and prevents higher trends from overlapping with lower trends expressed as follows,

$$H = \frac{x - \mu_x}{\delta} \tag{1}$$

The preprocessed data of the disease prediction model has the dimensionality of $\left[n \times 11\right]$.

3.3 SMOTE oversampling

SMOTE is a method of oversampling that creates artificial samples from the minority class and reduces the data insufficiency problem for which the pre-processed data is fed as the input. The process then trains the classifier utilizing a synthetically class-balanced or nearly class-balanced training set. The sample from the minority class H_i , and T randomly chosen samples from the neighborhood H_i^q , in which $q = 1,..T$, new synthetic samples s_i^{*q} are obtained as follows,

$$s_i^{*q} = H_i + r\left(H_i^q - H_i\right) \tag{2}$$

where r is a randomly generated number between the range 0 to 1.

3.4 Disease prediction using an Adaptive ensembled deep CNN-BilSTM classifier model

The Adaptive ensembled deep CNN-BilSTM classifier model comprises the deep CNN and BiLSTM models that are employed for disease prediction for which the balanced heart disease dataset is fed as the input. The developed classifier is formed by the fusion of the interactive hunt-deep CNN classifier and WoM-based deep BiLSTM classifier, which offers higher prediction accuracy with less training time for disease prediction. Equation (3) illustrates the results of the hybrid optimum learning model, which utilizes the efficient performance of both the fused models during disease prediction.

$$Y^* = \psi * O_{cnn} + \zeta * O_{lstm} \tag{3}$$

where ψ and ζ are the fusion parameters, Y^* is the output of the adaptive ensemble deep CNN-BiLSTM classifier, O_{cnn} and O_{lstm} are the output of interactive hunt-deep CNN andWoM–based deep BiLSTM respectively.

3.4.1. Interactive hunt-deep CNN classifier

CNN is one of the most widely utilized AI systems due to its excellent capacity to automatically recognize the features distributed within the data. The interactive hunt-deep CNN uses the interactive hunt optimization that optimizes the deep CNN parameters. The output of the CNN is formulated as follows:

$$O_{cnn} = Z(s_i * V^k + \beta^k) \tag{4}$$

where β^k and V^k is the bias of the k^{th} convolution (conv) layer, Z is the activation function, and s_i is the input parameter. The learning model of deep CNN is performed utilizing the interactive hunt optimization, which uses the update rule as formulated in equation (5).

$$D_{cnn} = 0.5P_S\left[1 - E.f.S\right] + 0.5P_{IH}\left(1 - Ef - fM_{\max}\right) + 0.5\left[f \times M_{\max} \times P_D\right] \tag{5}$$

where the position of the hybrid interactive hunting search agents is denoted as D_{cnn} and P_S is the successor position, P_{IH} is the interactive hunter position at (y^{th})iteration, f is an arbitrary number between 0 and 1,

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

$M_{\max}$ is the maximum movement towards the dominating search agent, E and S represents the co-efficient vectors and P_D is the position of the dominating search agent. The layer details of the classifier are depicted in Table 1.

Table 1: Layer details of the CNN classifier

1	'input'	Sequence Input	Sequence input with 100 dimensions
2	'fold'	Sequence Folding	Sequence folding
3	'conv1'	Conv layer	16 21×1 convolutions with stride [1 1] and padding 'same'
4	'maxpool1'	Max Pooling	7×1 max pooling with stride [7 7] and padding 'same'
5	'conv2'	Conv layer	32 17×1 convolutions with stride [1 1] and padding 'same'
6	'maxpool2'	Max Pooling	6×1 max pooling with stride [6 6] and padding 'same'
7	'conv3'	Conv layer	64 13×1 convolutions with stride [1 1] and padding 'same'
8	'maxpool3'	Max Pooling	7×1 max pooling with stride [7 7] and padding 'same'
9	'unfold'	Sequence Unfolding	Sequence unfolding
10	'flatten'	Flatten	Flatten
11	'bilstm1'	BiLSTM	BiLSTM with 10 hidden units
12	'FC'	Fully Connected	2 fully connected layer
13	'softmax'	Softmax	softmax
14	'classification'	Classification Output	crossentropyex

3.4.2. WoM-based deep BiLSTM classifier

BiLSTM is a subtype of Recurrent neural networks(RNNs) that has recently made a splash in the DL for disease prediction. The WoM-based deep BiLSTM classifier is utilized for efficient decision-making and secure data transfer of heart disease prediction. Most of the existing disease prediction models are affected by the issues of prediction accuracy, applicability, and challenging hyperparameter design that impact the decision model. The BiLSTM model is employed that takes into account the contextual information of time-series data. Additionally, the merits of WoM involve the local optima avoidance and global optima reaching effectively boost the deep BiLSTM model. The BiLSTM is defined as follows,

$$O_{lstm} = V_{K''u} K^{L''} + V_{K'u} K^{L'} + \beta_u \tag{6}$$

where BL_{out} is the output of the BiLSTM, $K^{L''}$ and $K^{L'}$ are the hidden layers output in the forward and backward directions respectively for all stack levels L. The update rule for training the deep Bi-LSTM parameters utilizing the WoM optimization is formulated in eqn. (7)

$$U_{WoM} = \begin{cases} U^i(T) + C_{FLOW}\left[G_{\min} + N_y \otimes \left[G_{\max} - G_{\min}\right]\right] \otimes R; & if\ h \le F_n \\ U^i(T) + \left[F_n(1-h) + h\right]\left[U_{h1}(T) - U_{h2}(T)\right] \quad ; & if\ h > F_n \end{cases} \tag{7}$$

Where U_{WoM} is the attained appropriate solution for the position vector U, U^i is the initial position vector of the crookback whales. The effects of counter flow are designated as C_{FLOW}, $G_{\min}$ and $G_{\max}$ are the lower and upper bands, $h1$ and $h2$ are the random indexes of $U(T)$.

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

3.4.3 Adaptive optimization

Adaptive optimization is developed for declaring the fusion parameters ψ and ζ through adaptive tuning enabled hybrid swarm optimization that is developed through the characters of duck and fish optimizations [22] [23]. The proposed adaptive optimization initializes the path for determining the best solution concerned with the attained fitness of the individual candidates. The fitness solution is boosted by incorporating the random search, seeking, attack prohibition, following, and waiting that explores the optimum solution. The solution of the adaptive optimization is initialized as Q, which contains the fusion parameters ψ and ζ.

$$Q = [\psi, \zeta] \tag{8}$$

The adaptive rule for fusion parameters of the ensemble model is formulated in eqn. (9) as follows.

$$Q^{T+1} = \begin{cases} Q^{\omega} + V_l * (Q_{per} - \rho Q^{\omega}), & if\ p \le 0.25 \\ 0.5\left[Q_l^{\omega}(2 + B - X_1 + X_2) + X_1 O - X_2 Q_e\right], & if\,(0.25 \le p \le 0.5) \\ Q_{\omega} + g_1(d^{\omega}), & if\,(0.5 > p \le 0.75) \\ Q^{\omega} - p_{vol} * \psi * \left[\dfrac{Q^{\omega} - Q_{avg}}{W(Q^{\omega} - Q_{avg})}\right], & if\,(0.75 > p \le 0.9) \\ 0.5\left[Q_r - B.W + Q_l^{\omega} + w_1(O - Q_i^{\omega}) + w_2(Q_i^{\omega} \pm Q_{pos})\right], & if\,(p > 1) \end{cases} \tag{9}$$

where the personal best position is represented as Q_{per} , Q_r indicates the random position of the candidate. The food search direction is described as B , and the distance between the l_{th} candidate as well as food source is indicated as W , leader candidate is represented as O. w_1 and w_2 are the competitive and cooperative behavior of the candidates. Then the values of w_1 and w_2 are find out adaptively in which the weighing factor V_l lies in the range $[0,1]$

$$w_1 = Q_{\max} * \left(1 - \frac{rand(Q^{\omega}, Q_{\max})}{Q_{\max}}\right) \tag{10}$$

where $Q_{\max}$ is the position corresponding to the maximal fitness and Q^{ω} is the current position.

$$V_l = V_{\min} + (V_{\max} - V_{\min}) \times \frac{\omega_{\max} - \omega}{\omega_{\max} - 1} \tag{11}$$

where, $V_{\min}$ is the minimal assigned weight during iteration, $V_{\max}$ is the maximal weight assigned during iteration $\omega_{\max}$ is the maximum iteration.

$$w_2 = Q_{\min} * \left(1 - \frac{rand(Q^{\omega}, Q_{\min})}{Q_{\min}}\right) \tag{12}$$

where, $Q_{\min}$ is the position corresponding to the worst fitness values.

$$\psi = \psi_{\max} - \frac{t * (\psi_{\max} - \psi_{\min})}{t_{\max}} \tag{13}$$

The fitness is evaluated based on the model accuracy, which should be higher for the best solution as follows,

$$fit(Q) = \max\left(acc\left(Y^*\right)\right) \tag{14}$$

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

4. Results and discussion

The proposed framework for smart heart disease prediction is executed and the results are assessed for evaluating the efficacy of the model.

4.1 Experimental setup

The experimentation is executed in MATLAB software running on the Windows 10 Operating system with 8GB RAM Internal memory. The implementation utilizes the heart disease dataset [19] and the UCI heart disease dataset [20] for testing and training the classifier.

4.1.2 Dataset description

The heart disease dataset [19]: The dataset was generated by fusing many datasets that were previously available and the integrated dataset includes 11 common features. The following five datasets were used to implement the disease and their corresponding numbers of instances are stated as follows, Cleveland:303 Hungarian: 294 Switzerland: 123 Long Beach VA: 200 Stalog (Heart) Data Set: 270 that are utilized for better performance for heart disease prediction.

UCI heart disease dataset[20]: The dataset includes 4 databases: Cleveland, Hungary, Switzerland, and the VA Long Beach. The DS has Multivariate Dataset Characteristics and is utilized for classification Tasks, Feature Type involves Categorical, Integer, and Real along with 303 instances and 13 features that are implemented for efficient classification of heart disease prediction.

4.2 Experimental analysis

The experimental results of the Adaptive ensembled deep CNN-BilSTM for disease prediction are discussed in the below section

4.2.1Performance metrics

The metrics are utilized for assessing the efficacy of the model and the employed metrics for evaluating the disease prediction model are explained as follows

a)Accuracy

Accuracy is the ratio of accurate prediction to the overall prediction of the data instances and is expressed as follows,

$$Acc = \frac{tp + tn}{tp + tn + fp + fn} \tag{18}$$

b)Sensitivity(Sen)

Sensitivity evaluates the ability of the model to predict the true positives of the available category.

$$Sen = \frac{tp}{tp + fn} \tag{19}$$

c)Specificity(Spec)

Specificity evaluates the ability of the model to predict the true negatives of the available category.

$$Spec = \frac{tn}{tn + fp} \tag{20}$$

d) F-measures(F-ms)

f-ms evaluates the measure of the model's accuracy over the dataset.

$$F - ms = \frac{2tp}{2tp + fp + fn} \tag{21}$$

where tp is True positive, tn is True Negative, fp is False Positive and fn is the False Negative.

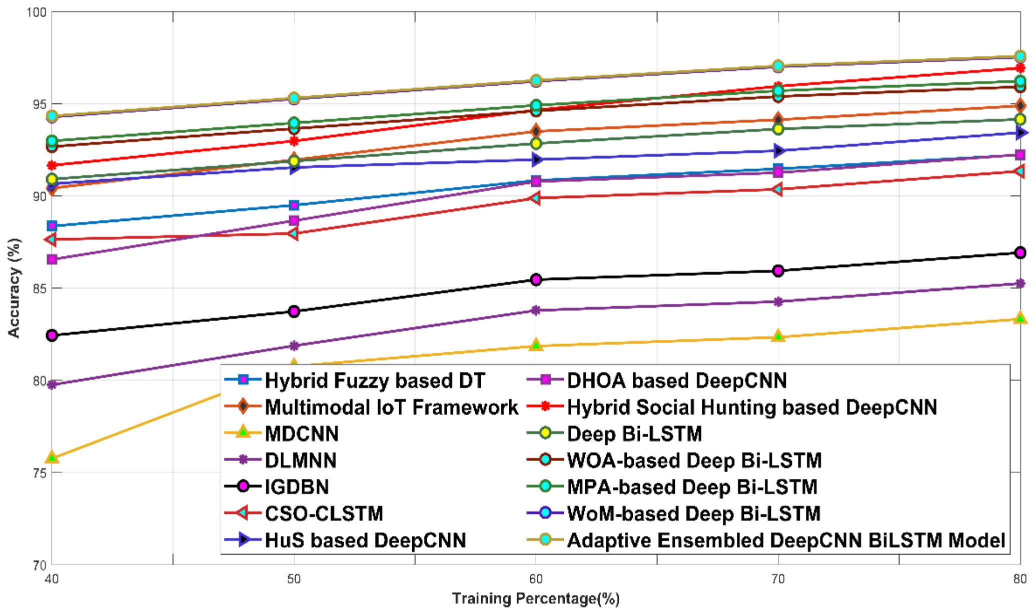
Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

4.3. Comparative analysis:(make comparative analysis in tabular form)

The section portrays the comparative analysis of the techniques employed for heart disease prediction. The proposed method is evaluated and compared with some existing methods in heart disease prediction like Hybrid Fuzzy DT[24], Multimodal IoT[28], MDCNN[5]], DLMNN[6], IGDBN, CSO-CLSTM[7], DHOA based deep CNN[8], Deep BiLSTM[9], HuS based deep CNN, hybrid social hunt deep CNN, WoA based deep BiLSTM [10], MPA based Deep BiLSTM and WoM based deep BiLSTM.

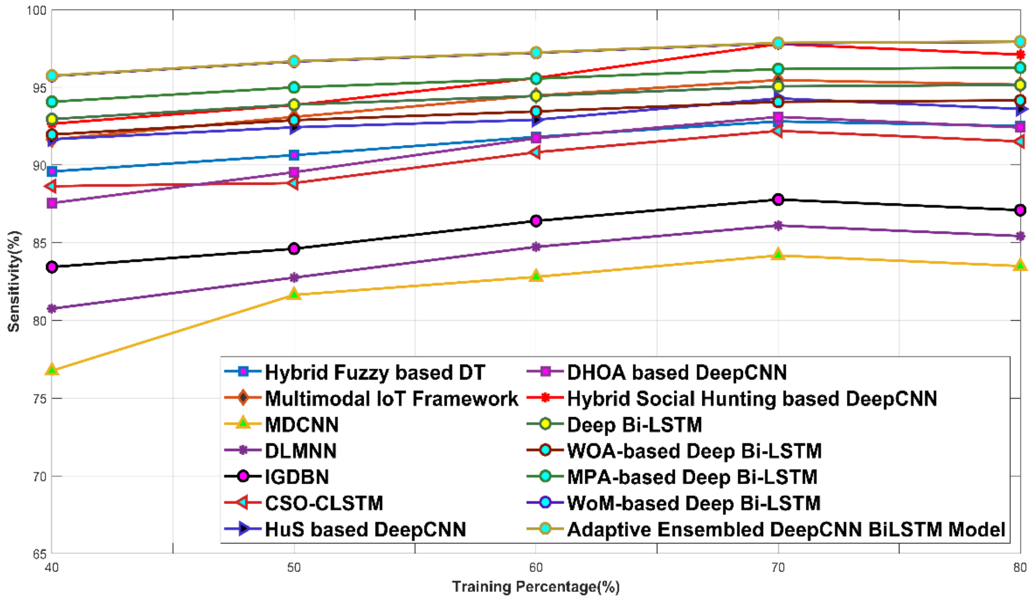
4.3.1.Comparative analysis concerning DS-1

The comparative analysis is performed concerning the DS-1 as shown in Figure 2. The accuracy of the adaptive ensembled deep CNN-BilSTM at Training percentage(TP) 80% is 97.573%, which shows 5.483% improvement over the existing hybrid Fuzzy DT technique, 2.757% over Multimodal IoT, 14.607% over MDCNN, 12.628% over DLMNN, 10.918% over IGDBN,6.388% over CSO-CLSTM,4.247% over HuS based deep CNN,5.466% over DHOA based deep CNN,0.660% over hybrid social hunt deep CNN,3.507% over Deep BiLSTM,1.699% over WoA based deep BiLSTM,1.384% over MPA based Deep BiLSTM, and 0.0487% over WoM based deep BiLSTM. The sensitivity of the adaptive ensembled deep CNN-BilSTM at TP 80% is 97.949 % which shows 5.552% improvement over the existing hybrid fuzzy DT,2.836% over Multimodal IoT, 14.755% over MDCNN, 12.783% over DLMNN,11.079% over IGDBN,6.567% over CSO-CLSTM,4.434% over HuS based deep CNN,5.649% over DHOA based deep CNN,0.861% over hybrid social hunt deep CNN,2.857 % over Deep BiLSTM,3.874% over WoA based deep BiLSTM,1.719% over MPA based deep BILSTM and 0.0242% over WoM based Deep BiLSTM. Additionally, the specificity of the adaptive ensembled deep CNN-BilSTM at TP 80% is 97.592 % which shows 5.406% improvement over the existing hybrid fuzzy DT, 2.680% over Multimodal IoT, 14.428% over MDCNN, 12.449% over DLMNN,10.739% over IGDBN,6.210% over CSO-CLSTM,4.070% over HuS based deep CNN,5.288% over DHOA based deep CNN,0.483% over hybrid social hunt deep CNN,4.178 % over deep BiLSTM,2.487% over WoA based deep BiLSTM,0.694% over MPA based Deep BiLSTM and 0.073% over WoM based deep BiLSTM. Additionally, the F-ms at TP 80% is 97.705 % which shows 5.480% improvement over the existing hybrid fuzzy DT, 2.758% over Multimodal IoT, 14.597% over MDCNN, 12.620% over DLMNN,10.912% over IGDBN,6.389% over CSO-CLSTM,4.251% over HuS based deep CNN,5.468% over DHOA based deep CNN,0.668% over hybrid social hunt deep CNN,3.513 % over Deep BiLSTM,2.688% over WoA based deep BiLSTM and 1.266% over MPA based deep BILSTM and 0.048% over WoM based Deep BiLSTM. The analysis proves that the developed technique outperformed the existing techniques.

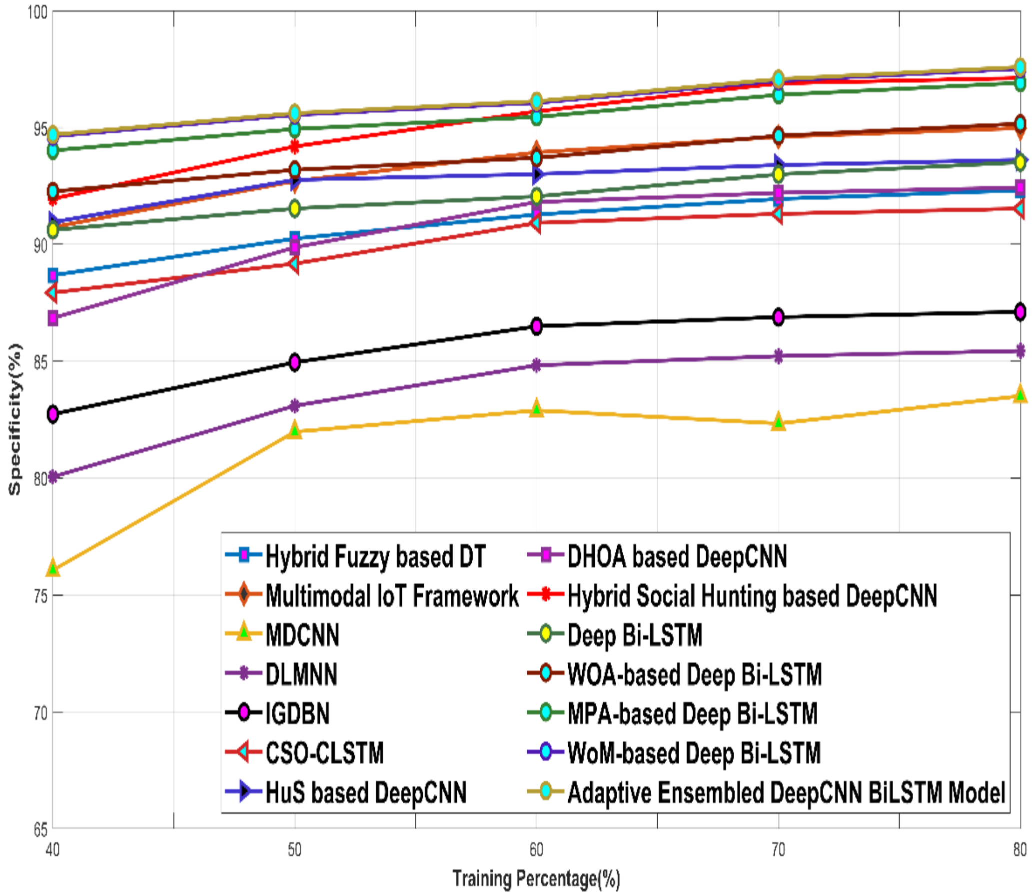


(a)

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

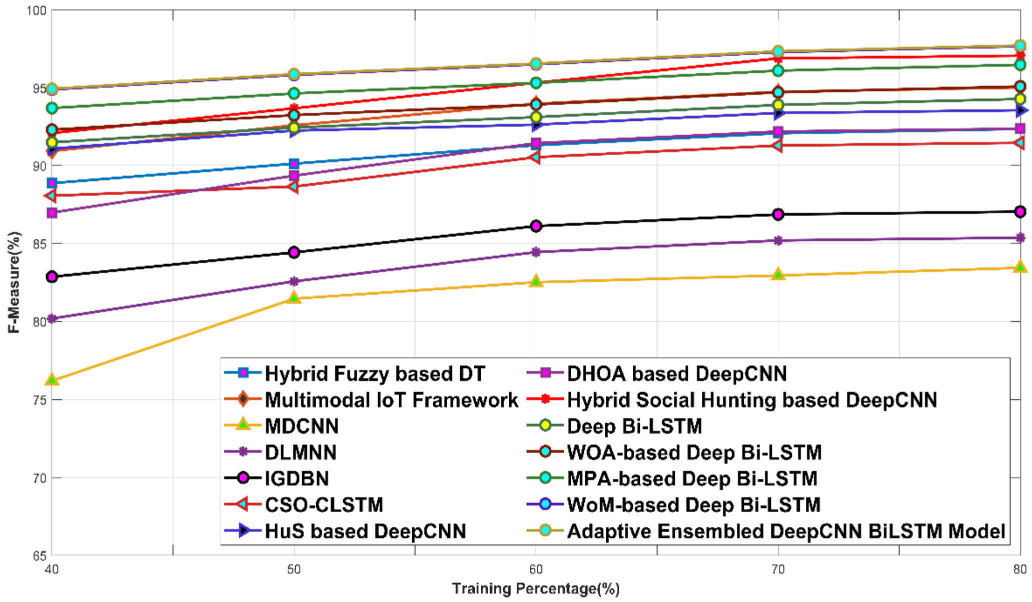


(b)



(c)

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023



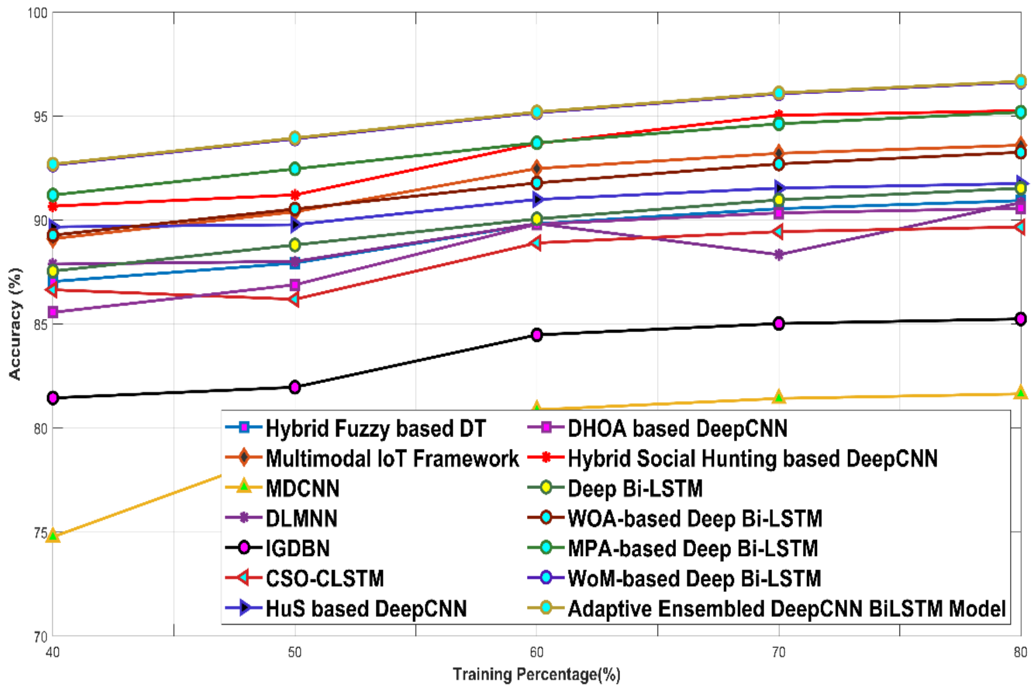
(d)

Figure 2:Comparative analysis concerning DS-1 in terms of a) accuracy b)sensitivity c)specificity d)f-ms

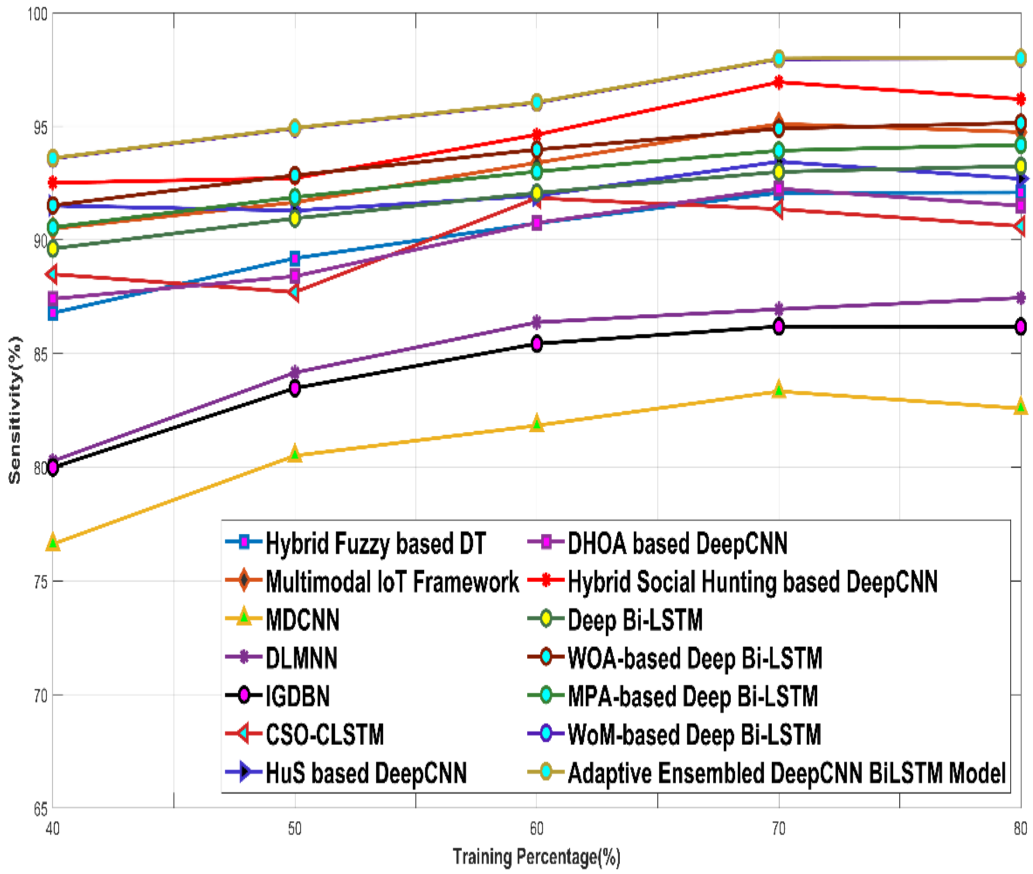
4.3.2. Comparative analysis concerning DS-2 (in tabular form)

The comparative analysis is performed concerning the DS-2 as shown in Figure 3. The accuracy of the adaptive ensembled deep CNN-BilSTM at Training percentage (TP) 80% is 96.666% which shows 5.929% improvement over the existing hybrid fuzzy DT, 3.1776 %over Multimodal IoT, 15.540 % over MDCNN, 6.031% over DLMNN, 11.815% over GDBN,7.243% over CSO-CLSTM, 5.082% over HuS based deep CNN,6.312% over DHOA based deep CNN,1.461% over Hybrid social hunt deep CNN,5.314% over Deep BiLSTM,3.527% over WoA based deep BiLSTM,1.533% over MPA based deep BILSTM and 0.0423% over WoM based deep BiLSTM. While, the sensitivity of the adaptive ensembled deep CNN-BilSTM at TP 80% is 98.012% which shows 6.042% improvement over the existing hybrid fuzzy DT,3.328 % over Multimodal IoT, 15.737% over MDCNN, 10.774% over DLMNN,12.063 % overIGDBN,7.554 % over CSO-CLSTM,5.423 % over HuS based deep CNN,6.636% over DHOA based deep CNN,1.852 % over Hybrid social hunt deep CNN,4.856 %over Deep BiLSTM,2.918 % over WoA based deep BiLSTM, 3.901% over MPA based deep BILSTM and 0.020%over WoM based deep BiLSTM. Additionally, the specificity of the adaptive ensembled deep CNN-BilSTM at TP 80% is 97.187 % which shows 5.684 % improvement over the existing hybrid fuzzy DT, 2.948 % over Multimodal IoT, 15.010% over MDCNN, 8.986% overDLMNN,11.306% overIGDBN,6.758%over CSO-CLSTM,4.609% over HuS based deep CNN,5.833% over DHOA based deep CNN,1.008% over Hybrid social hunt deep CNN,5.174% over Deep BiLSTM,4.118% over WoA based deep BiLSTM and 1.068% over MPA based deep BILSTM and 0.063%over WoM based Deep BiLSTM. Additionally, the F-ms of the adaptive ensembled deep CNN-BilSTM at TP 80% is 97.288 % which shows 5.885% improvement over the existing hybrid fuzzy DT, 3.151% over Multimodal IoT, 15.430% over MDCNN, 8.608% over DLMNN,11.729 % over IGDBN,7.186 % overCSO-CLSTM,5.039 % over HuS based deep CNN,6.261% over DHOA based deep CNN,1.441 % over Hybrid social hunt deep CNN,5.114 % over Deep BiLSTM,3.519 % over WoA based deep BiLSTM and 2.173% over MPA based deep BILSTM and 0.042% over WoM based deep BiLSTM. The analysis proves that the proposed technique outperformed the existing techniques.

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

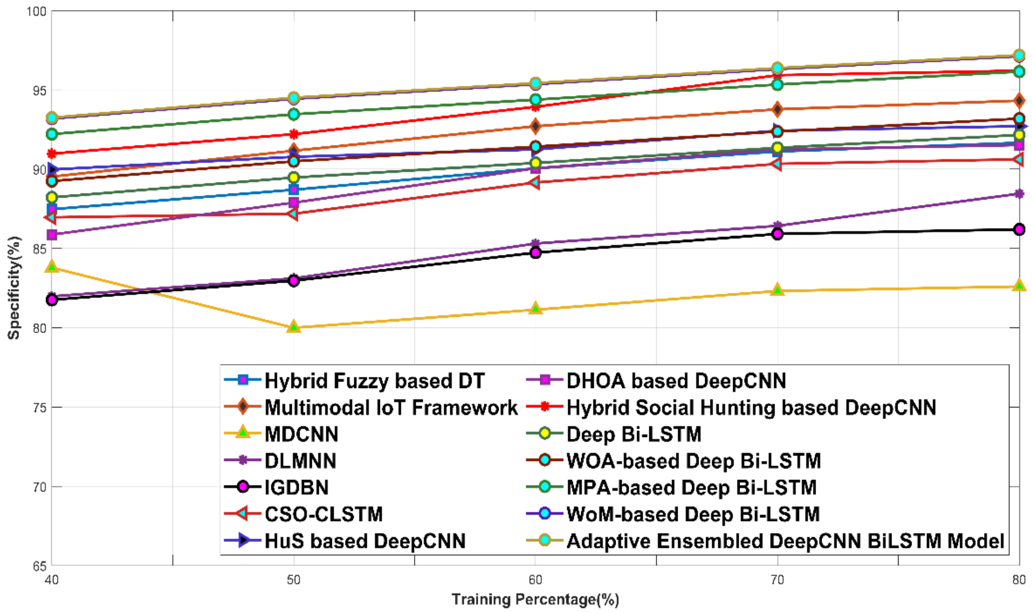


(a)

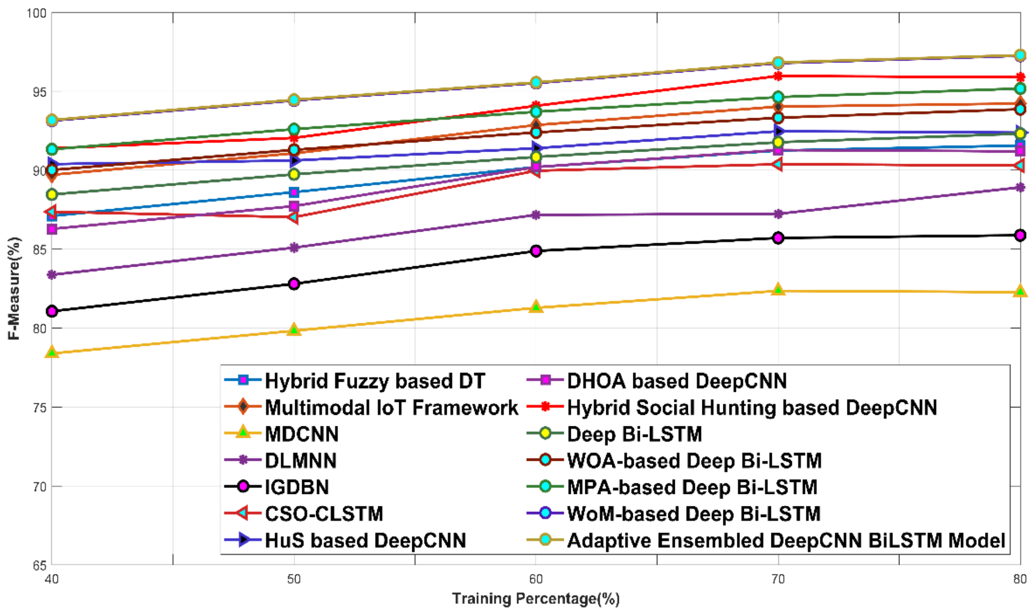


(b)

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023



(c)



(d)

Figure 3: Comparative analysis concerning DS-2 in terms of a) accuracy b)sensitivity c)specificity d)f-ms

4.3.3 Comparative discussion

The analysis of the multiple heart disease prediction techniques is enclosed briefly in this section. The techniques, such as Hybrid Fuzzy DT, Multimodal IoT, MDCNN, DLMNN, IGDBN, CSO-CLSTM, and so on are utilized for comparative analysis. The hybrid fuzzy DT method [24], in which more rules increased the complexity of the model, meanwhile fewer rules reduced the accuracy, and the DT caused the overfitting of data. Multimodal IoT [28] performance is limited due to the bias and privacy issues along with the different heterogeneous data that affect the efficiency of the model. In the MDCNN method, testing the sensor values takes more time to predict the disease, as well as erroneous results, are obtained in the prediction that limited the performance [14]. The modified DCNN technique has limited the prediction accuracy due to a lack of consideration of the pathological factors[5]]. Additionally, the DLMNN provides higher accuracy but requires more training time to train the prediction model with massive patient data collected from IoT [6]. In the CSO-CLSTM method, the performance is limited due to the limited efficiency and accessibility of the data from

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

IoT[7]. DHOA-based deep CNN has the limitation of low accuracy due to the dimension reduction of features [8]. While comparing methods using different classifiers, the proposed method overcame the above challenges by employing the efficient feature extraction and classification model. The performance of the superior techniques along with the developed method is demonstrated here, and the data from the DS-1 and DS-2 are utilized for the comparative evaluation. Table 2 demonstrates the comparative discussion of the proposed method over the existing methods.

Table 2: Comparative discussion of the DS-1 and DS-2

Analysis/Methods	DS-1				DS-2			
	Accuracy (%)	**sensitivity (%)**	**Specificity (%)**	**F-ms (%)**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F-ms (%)**
Hybrid Fuzzy DT	92.228	92.511	92.316	92.350	90.934	92.089	91.662	91.562
Multimodal IoT	94.882	95.170	94.976	95.01	93.594	94.749	94.321	94.221
MDCNN	83.319	83.496	83.511	83.442	81.644	82.587	82.598	82.276
DLMNN	85.251	85.427	85.442	85.373	90.835	87.451	88.452	88.913
IGDBN	86.92	87.096	87.111	87.042	85.244	86.187	86.198	85.876
CSO-CLSTM	91.339	91.516	91.531	91.462	89.664	90.607	90.618	90.296
HuS-based deep CNN	93.428	93.605	93.620	93.551	91.753	92.696	92.707	92.3
DHOA-based deep CNN	92.239	92.416	92.431	92.362	90.563	91.507	91.518	91.196
Hybrid social hunt deep CNN	96.928	97.105	97.120	97.051	95.253	96.196	96.207	95.885
Deep BiLSTM	94.151	95.151	93.515	94.272	91.528	93.252	92.158	92.312
WoA-based deep BiLSTM	95.915	94.154	95.165	95.078	93.256	95.151	93.184	93.864
MPA-based deep BiLSTM	96.221	96.265	96.915	94.467	95.184	94.188	96.148	95.173
WoM-based deep BiLSTM	97.525	97.925	97.521	97.657	96.625	97.991	97.125	97.247
Adaptive ensembled deep CNN-BilSTM	97.573	97.949	97.592	97.705	96.666	98.012	97.187	97.288

5. Conclusion

The research employs the adaptive ensembled deep CNN-BiLSTM framework in IoT that is developed by combining the characteristics of the interactive hunt-based deep CNN and WoM-based deep BilSTM that enhanced the efficacy of heart disease prediction. Additionally, the adaptive optimization developed in the method tuned the fusion parameters of the classifier which enhanced the accuracy of disease prediction. The privacy of the sensitive patient data utilized for heart disease prediction is boosted with the ECC-based modified Diffi Huffman encryption and decryption algorithm. Hence the developed IoT-based heart disease prediction model assists the medical experts in diagnosing the disease at the earlier stage. The performance of the Adaptive ensemble deep CNN-BiLSTM method is compared and evaluated in terms of accuracy, sensitivity, specificity, and f-measures as 97.573%,98.012%, 97.592%, and 97.705% respectively that demonstrated the efficacy of the method with other existing techniques. In the IoT platform, it is significant to ensure security and robustness hence in the future a model that protects against cyber threats will be developed. In the future, the model will be developed to handle multi-class and more extensive medical data.

References

[1] Diller, G.P., Kempny, A., Babu-Narayan, S.V., Henrichs, M., Brida, M., Uebing, A., Lammers, A.E., Baumgartner, H., Li, W., Wort, S.J. and Dimopoulos, K., Machine learning algorithms estimating

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

prognosis and guiding therapy in adult congenital heart disease: data from a single tertiary centre including 10 019 patients. European heart journal, 40(13), 1069-1077, 2019.
[2] Junejo, A.R., Shen, Y., Laghari, A.A., Zhang, X. and Luo, H., Notice of Retraction: Molecular Diagnostic and Using Deep Learning Techniques for Predict Functional Recovery of Patients Treated of Cardiovascular Disease. IEEE Access, 7, 120315-120325, 2019.
[3] Pan, Y., Fu, M., Cheng, B., Tao, X., and Guo, J., Enhanced deep learning assisted convolutional neural network for heart disease prediction on the internet of medical things platform. Ieee Access, 8, 189503-189512, 2020.
[4] Poplin, R., Varadarajan, A.V., Blumer, K., Liu, Y., McConnell, M.V., Corrado, G.S., Peng, L. and Webster, D.R., Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. Nature biomedical engineering, 2(3), 158-164, 2018.
[5] Zhang, Z., Qiu, Y., Yang, X. and Zhang, M., Enhanced character-level deep convolutional neural networks for cardiovascular disease prediction. BMC medical informatics and decision making, 20(3), 1-10, 2020.
[6] Sarmah, S.S., An efficient IoT-based patient monitoring and heart disease prediction system using deep learning modified neural network. Ieee access, 8, 135784-135797, 2020.
[7] Jha, S., Artificial intelligence and Internet of Things for sustainable healthcare system. Journal of Sustainable Science and Transformative Research-Reviews & Letters, 1(2), 44-50, 2022.
[8] Ha, W. and Vahedi, Z., Automatic breast tumor diagnosis in MRI based on a hybrid CNN and feature-based method using improved deer hunting optimization algorithm. Computational Intelligence and Neuroscience, 2021.
[9]Nancy, A.A., Ravindran, D., Raj Vincent, P.D., Srinivasan, K. and Gutierrez Reina, D., Iot-cloud-based smart healthcare monitoring system for heart disease prediction via deep learning. Electronics, 11(15), 2292, 2022.
[10]Yang, X. and Li, S., Prediction of COVID-19 Using a WOA-BILSTM Model. Bioengineering, 10(8), 883, 2023
[11] Dang, L.M., Piran, M.J., Han, D., Min, K. and Moon, H., A survey on internet of things and cloud computing for healthcare. Electronics, 8(7), 768, 2019.
[12]Ahmed, F., An Internet of Things (IoT) application for predicting the quantity of future heart attack patients. International Journal of Computer Applications, 164(6), 36-40, 2017.
[13] Sidheeque, A., Kumar, A., Balamurugan, R., Deepak, K.C. and Sathish, K., Heartbeat sensing and heart attack detection using Internet of Things: IoT. Int. J. Eng. Sci. Comput, 7(4), 6662-6666, 2017.
[14] Khan, M.A., An IoT framework for heart disease prediction based on MDCNN classifier. IEEE Access, 8, 34717-34727, 2020.
[15] Lim, T.S., Loh, W.Y. and Shih, Y.S., A Comparison of Prediction Accuracy, Complexity, and Training Time of Thirty-three Old and New Classification Algorithms, Department of Statistics, University of Wisconson, Madison, 1999.
[16]Datta, P. and Sharma, B., A survey on IoT architectures, protocols, security and smart city based applications. In 2017 8th International conference on computing, communication and networking technologies (ICCCNT). 1-5, 2017
[17] Tuli, S., Basumatary, N. and Buyya, R., Edgelens: Deep learning based object detection in integrated iot, fog and cloud computing environments. In 2019 4th International Conference on Information Systems and Computer Networks (ISCON) 496-502, 2019,
[18] Verma, P., Tiwari, R., Hong, W.C., Upadhyay, S. and Yeh, Y.H., FETCH: a deep learning-based fog computing and IoT integrated environment for healthcare monitoring and diagnosis. IEEE Access, 10, 12548-12563, 2022.
[19] https://www.kaggle.com/sid321axn/heart-statlog-cleveland-hungary-final
[20] https://archive.ics.uci.edu/ml/datasets/heart+disease
[21] Rosy, J.V. and Kumar, S.B.R., Optimized encryption based elliptical curve Diffie-Hellman approach for secure heart disease prediction. International Journal of Advanced Technology and Engineering Exploration, 8(83), 1367, 2021.
[22] Barani, A.M., Latha, R. and Manikandan, R., Implementation of Artificial Fish Swarm Optimization for Cardiovascular Heart Disease. International Journal of Recent Technology and Engineering (IJRTE), 8(4S5), 134-136, 2019.
[23] Zhang, M., Wen, G. and Yang, J., Duck swarm algorithm: a novel swarm intelligence algorithm. arXiv preprint arXiv:2112.13508. 2021.
[24] Pati, A., Parhi, M., Alnabhan, M., Pattanayak, B. K., Habboush, A. K., & Al Nawayseh, M. K. (2023, February). An IoT-Fog-Cloud Integrated Framework for Real-Time Remote Cardiovascular Disease Diagnosis. In Informatics (Vol. 10, No. 1, p. 21). MDPI.

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023

[25] Sarmah, S.S., An efficient IoT-based patient monitoring and heart disease prediction system using deep learning modified neural network. Ieee access, 8, 135784-135797, 2020.
[26] Tuli, S., Basumatary, N., Gill, S.S., Kahani, M., Arya, R.C., Wander, G.S. and Buyya, R., HealthFog: An ensemble deep learning based Smart Healthcare System for Automatic Diagnosis of Heart Diseases in integrated IoT and fog computing environments. Future Generation Computer Systems, 104, 187-200, 2020.
[27] Maldonado, S., Julio L., and Carla V., An alternative SMOTE oversampling strategy for high-dimensional datasets. Applied Soft Computing 76, 380-389, 2019
[28] Moshawrab, M., Adda, M., Bouzouane, A., Ibrahim, H. and Raad, A., Reviewing Multimodal Machine Learning and Its Use in Cardiovascular Diseases Detection. Electronics, 12(7), 1558, 2023.

[29] Nadeem, M. W., Goh, H. G., Khan, M. A., Hussain, M., & Mushtaq, M. F. (2021). Fusion-Based Machine Learning Architecture for Heart Disease Prediction. Computers, Materials & Continua, 67(2).

Doi: https://doi.org/10.54216/FPA.140104
Received: June 01, 2023 Revised: September 04, 2023 Accepted: November 04, 2023