An Innovative Approach to Cardiovascular Disease Prediction: A Hybrid Deep Learning Model

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ABSTRACT

The increasing prevalence of cardiovascular disorders has created an imperative need for accurate diagnoses. Despite the emergence of numerous techniques for disease classification and secure data transmission, a prevailing shortcoming is the lack of precision in decision-making. This study aimed to address this critical issue by introducing an innovative disease prediction model that uses a hybrid classifier. The proposed hybrid classifier combined deep Bidirectional Long-Short-Term Memory (deep Bi LSTM) and deep Convolutional Neural Network (deep CNN).To further improve its performance, the proposed approach employed hybridized swarm optimization to fine-tune fusion parameters and optimize the learning model for enhanced accuracy. This study focused on heart disease as its central concern, strengthening data security through the implementation of Diffi-Huffman based on Elliptic Curve Cryptography (ECC) during data transmission. The resulting automatic disease prediction model adopted the hybrid deep classifier, which was born from the amalgamation of two components: the interactive hunt-deep CNN classifier and the WoM-deep Bi LSTM. The proposed hybrid learning model achieved impressive accuracy, F-measure, sensitivity, and specificity of 97.716%, 97.848%, 98.021%, and 97.807%, respectively, marking a significant advance in the realm of cardiovascular disease prediction.

Keywords-cardiovascular disease prediction; elliptic curve cryptography; interactive hunt-deep CNN; WoM-deep bi LSTM; Diffi-Huffman

I. INTRODUCTION

Data gathering and storage have been digitalized on a large scale because of recent advances in information science, using tools such as mobile devices, laptops, satellite reports, and so on for data collection. These data include private personal information such as medical records and others [1]. When patients seek treatment in different facilities, reliable and prompt medical precaution facilities are provided at any time through the exchange of electronic health records without redundancy [2]. The Internet of Things (IoT) plays an important role in helping physicians [3-4]. The IoT may virtually connect people and objects in the age of the fast Internet to exchange information. IoT devices are integrated into several web applications for data collection. It is crucial for real-time health observation systems that the network remains mobile and offers efficient client-server communication. As a result, it is essential to keep track of individual sensor information in the web-based control system [5-6]. In addition, IoT and cloud computing technology are interdependent and have become beneficial areas for remotely managing the patient's condition to provide ongoing facilities by providing helpful information to patients and clinicians [7]. Many services use cloud solutions and machine learning algorithms to keep and process patient data [8-11]. In [2], a multi-objective successive approximation (EMSA) technique was introduced to maintain an adequate measure of privacy in healthcare clouds based on Euclidean L3P. In many cases, Wireless Personal

Area Network (WPAN) and Wireless Body Area Network (WBAN) data are protected using low-complexity algorithms [12]. In this rapidly evolving era of the Internet and fog servers, where a multitude of users and their private data are readily accessible, protecting healthcare data becomes an imperative priority. Security concerns are raised when patient health information is securely stored in an electronic format [13-15]. In [16], a security-dependent group mobility organization technique was proposed to secure sensitive information exchange. In [17], the AES-CFMAC and a motion practice were used to encourage data transfer between access points in a WBAN-based IoT network. In [10], an improved auto-categorical PSO was used for heart disease prediction. Initial accuracy challenges were attributed to limited medical records. In [5], a security-focused network handover technique was established using the AES-CFMAC algorithm, improving environmental descriptions while emphasizing the need to address power consumption and internet distribution. In [18], an EPPDA model was introduced that relied on authentication and permission phases using additively homomorphic encryption for data collection. In [1], SVD was applied to identify sensitive information using 3D RDP to balance data privacy and utility and requiring multiple perturbation techniques for improved classification. In [2], the EMSA algorithm was introduced to assess healthcare cloud privacy, focusing on role-based encryption keys to protect sensitive data. Hybridized swarm optimization is a technique to fine-tune the fusion parameters in a hybrid learning model that are crucial for its performance. In this process, the optimization method combines elements of swarm intelligence with other optimization techniques to effectively adjust the parameters. This hybridized approach relies on a pathfinder that assesses and adjusts the parameters based on their fitness, striving to identify the optimal solution while minimizing convergence and ensuring that the model performs optimally. Compared to existing methods, the hybrid learning model offers a unique approach to disease prediction with a focus on security and optimization. The inclusion of both deep CNN and Bi LSTM classifiers improves accuracy. The use of hybridized swarm optimization further improves parameter tuning based on fitness, increasing prediction effectiveness. However, more research is needed to assess the scalability and generalizability of the model to different medical sensor types. This study considered the current challenges for analyzing the effectiveness of a hybrid learning model:

- Current disease prediction models face challenges in early and accurate detection. Many proposed machine learning algorithms for disease prediction prioritize prediction without focusing on security concerns [19].
- Existing disease prediction methods often overlook feature selection, leading to reduced training efficiency [19]. Supervised machine learning algorithms have been used to identify heart rate variability signals.
- Predictive models are commonly based on multiple variables and manually calculated risk scores. While they perform well for the general population, their accuracy is limited when applied to all types of patients.

II. SMART HEALTHCARE SYSTEM MODEL

The proposed framework consists of three phases: data collection using distributed IoT nodes, device and patient authentication using the encryption scheme with a modified ECC-based Diffi-Huffman algorithm, and effective disease prediction using the collected data. In Figure 1, IoT nodes are initially deployed throughout the sensing environment to collect patient information for remote healthcare monitoring and predicting health statuses. After the data are collected, they undergo robust protection through encryption to protect them from potential intruders while residing in the cloud. Subsequently, the securely encrypted data are transmitted to the cloud server. There, healthcare professionals can access and examine health reports, using the information to formulate diagnoses and provide medical recommendations.

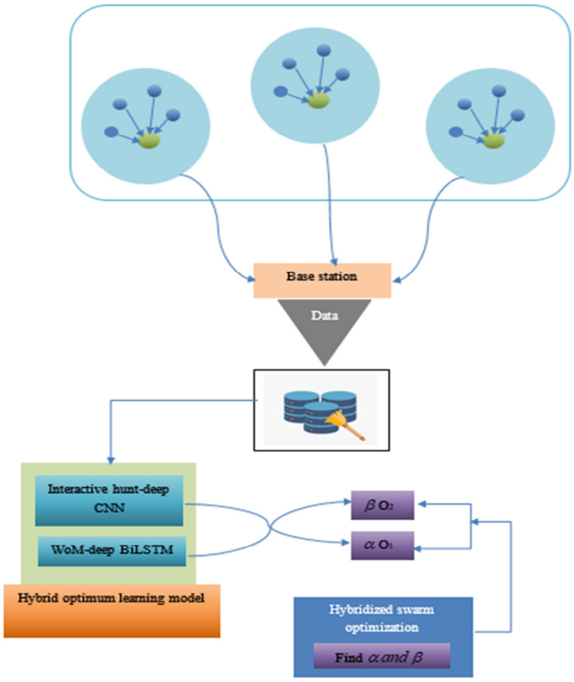

Fig. 1. Prediction of cardiac disease schematic form.

A. *Data Acquisition And Authentication*

Data acquisition is the process of gathering and combining data from all relevant sources. The acquired data must be encoded to protect the information in the cloud from unauthorized attackers who might access the stored information. The authentication process ensures the certification and validation of information before updating patient medical records securely on the cloud server. To achieve this, an algorithm is employed to encrypt both previously published and current medical reports. This encryption involves key generation and signature creation at the sender's end, followed by signature verification at the receiver's end. Subsequently, secure data transmission to the destination is accomplished using a modified ECC-dependent Diffi-Huffman method. At the destination, an authenticated doctor decrypts the data to provide a diagnosis for the patient.

B. Hybrid Learning Model For Disease Prediction

This study combined the interactive hunt-deep CNN classifier with the WoM-based Bi LSTM classifier in a hybrid learning model to train preprocessed heart disease data. Compared to a standard deep learning model, this hybrid approach achieves superior accuracy and efficiency by leveraging the combined performance of both classifiers. Equation (1) originates from the interactive hunt optimization technique, which effectively fine-tunes the deep CNN classifier's parameters. Meanwhile, (2) is the result of employing WoM optimization to fine-tune the parameters of the deep Bi LSTM classifier, leading to optimal accuracy in heart disease prediction. The methods involved in the hybrid learning model are not identical, generating two different outputs for every instant of disease prediction.

$$J_{HSH}^{x+1} = 0.5F^{SUS}[1 - B \bullet a \bullet I] + 0.5F_x(1 - Ba - aMM) + 0.5[a \times MM \times F_x^{DOM}] \quad (1)$$

where the position of the hybrid interactive hunting search agents is denoted as J_{HSH}^{x+1}, F^{SUS} is successor's position, F_x is the position of the interactive hunter at x^{th} iteration, a is an arbitrary number varying between 0 and 1, MM is the maximum movement towards the dominating search agent, B and I represent the co-efficient vectors, and F_x^{DOM} is the location of the dominating search agent.

$$\vec{Y^*}(T) = \begin{cases} Y^i(T) + CF\left[\vec{Q}_{min} + \vec{N} \otimes \left(\vec{Q}_{max} - \vec{Q}_{min}\right)\right] \otimes \vec{V}, & if\ u \leq fn \\ Y^i(T) + [fn(1-u) + u]\left(Y_{u1}(T) - Y_{u2}(T)\right), & if\ u > fn \end{cases} \quad (2)$$

where Y^* is the attained suitable solution for the position vector Y, and Y^i is the initial position vector of the crookback whales. The counterflow effects are denoted as CF. $\vec{Q}_{min}$ and $\vec{Q}_{max}$ are the lower and upper bands, and u_1 and u_2 are the random indexes of $Y(T)$. Accordingly, the automatic prediction developed for the disease will follow the hybrid deep classifier, developed through hybridizing the interactive hunt-deep CNN classifier and WoM-deep BiLSTM classifier. The hybridization is supported using the fusion parameters, and the optimization algorithm is designed for tuning the deep classifiers to acquire effective prediction results. The hybrid classifier was developed, for which the fusion factors were designed and also used for tuning optimization, which was reliant on the hybridized swarm optimization. The outcome of the hybrid learning model is shown in (3), which utilizes the effective performance of both the interactive hunt-deep CNN and WoM-deep Bi LSTM model during the disease prediction.

$$y = \alpha * J_{HSH}^{x+1} + \beta * \vec{Y^*}(T) \quad (3)$$

where α and β are the fusion parameters that are effectively determined and tuned by hybridized swarm optimization.

1) Proposed Hybridized Swarm Optimization for the Hybrid Classifier

In the proposed hybridized swarm optimization, the path initialization for identifying the better solution is based on the attained fitness of the pathfinder [20]. The fitness of an individual pathfinder is enhanced by incorporating random search, seeking, attack prevention, following, and waiting of the swarm involved in the exploration of the optimal solution [21]. In the seeking phase, the fish will go swiftly and immediately to an area where there is more food when it is discovered. In the attack prevention phase, fish instinctively group when swimming to avoid harm. In the following phase, when a swarm finds food, the others will chase after it to find the food dangling, and leaping behavior occurs when fish stagnate in one area. In the waiting behavior phase, swarms stay in a place to find food from other regions.

The traversing paths that the solutions are initially assumed and a specific pathfinder's fitness is assessed depending on the attained solutions, which is expressed as:

$$P = \{P_1, P_2, \ldots P_n\} \quad (4)$$

where the path identified by the pathfinder is denoted as P with n number of paths.

In the random search phase, the pathfinder arrives at a location with more food as a result of the path-sorting behavior. Each individual progressively disperses and begins looking for food in the search space within [0,1]. The following equation applies to this process when the available search space is greater than one:

$$\vec{Y}(\tau+1) = 0.5\left[\vec{Y}_r - \vec{A} \cdot \vec{D} + Y_i^\tau + M_1(L - Y_i^\tau) + M_2\left(Y_i^\tau \pm Y_{posiiton}\right)\right], \quad (S > 1) \quad (5)$$

where the personal best position is represented as $Y_{position}$, and $\vec{Y}_r$ denotes the random position of the pathfinder agent to find food. The angle or the direction of the food search is described by $\vec{A}$, the distance between the i^{th} pathfinder at Y_r and the food source is denoted as $\vec{D}$, and the leader swarm is represented as L. M_1 and M_2 are the competitive and cooperative behaviors of the pathfinder for determining the optimum solution in the search space S.

As a consequence of the random search, when the available search space of the pathfinder may not fulfill the requirement of the swarm in the group, the seeking phase occurs at the search space of $S \leq 0.25$. The exploration is significantly related to the fitness of an individual pathfinder's position and expressed as

$$Y^{\tau+1} = Y^\tau + w_i * \left(Y_{personal} - \alpha Y^\tau\right), (S \leq 0.25) \quad (6)$$

where the present position of the pathfinder is denoted as Y^τ, the weight factor as w_i, which is in the [0,1] range, the personal best solution is described as $Y_{personal}$, and the random number is represented as α in the range of [0,1].

During the exploration, the attack prevention technique is introduced by the swarm in the search space of $[0.25, 0.5]$, which looks for a path to prevent attack from enemies, and is expressed as:

$$Y_L^{\tau+1} = Y_i^\tau + A^\tau, \quad (0.25 \geq S \leq 0.5) \quad (7)$$

The waiting behavior of the swarm is expressed in (8), which stays in a place to find food from other possible regions in the search space range $[0.75, 0.9]$.

$$Y^{\tau+1} = Y^{\tau} - S_{vol} * \alpha * \left[\frac{Y^{\tau}-Y_{avg}}{D[Y^{\tau}-Y_{avg}]}\right], \ (0.75 \geq S > 0.9) \quad (8)$$

where Y_{avg} is the average position of the swarm and S_{vol} is the volume of the search space. The following equations combine the attack prevention behavior of the swarm in the effective path determination by the pathfinder Y_{PF}:

$$Y_{PF}^{\tau+1} = Y_i^{\tau} + N_1(L - Y_i^{\tau}) + N_2(Y_i^{\tau} - Y_j^{\tau}) \quad (9)$$

$$Y^{\tau+1} = 0.5[Y_L^{\tau+1} + Y_{PF}^{\tau+1}] \quad (10)$$

$$Y^{\tau+1} = 0.5[(Y_i^{\tau} + A^{\tau}) + Y_i^{\tau} + N_1(L - Y_i^{\tau}) + N_2(Y_i^{\tau} - Y_j^{\tau})] \quad (11)$$

$$Y^{\tau+1} = 0.5[Y_i^{\tau}(2 + A - N_1 + N_2) + N_1 L - N_2 Y_j^{\tau}] \quad (12)$$

where the leader swarm is represented as L with competitive and cooperative behaviors N_1 and N_2, and Y_j^{τ} represents the swarms around the pathfinder.

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Algorithm 1. Pseudocode for the hybridized swarm
optimization
Input: P = {P1, P2, …, Pn}
Output: Pbest
Initialize the traversing paths P = {P1, P2, …, Pn}
Sketch and sort the paths based on fitness
while (t < tmax)
  For all i < n
    Case 1: if (s ≤ 0.25)
      Call seeking behavior
    Else if (0.25 ≥ s ≤ 0.5)
      Call attack prevention
    Else if (0.5 ≥ s ≤ 0.75)
      Call following
    Else if (0.75 ≥ s ≤ 0.9)
      Call waiting
    Else (s > 1)
      Call exploration phase
  Evaluate fit(Pi)
  If fit(Pi) < fit(Pbest)
    Restore Pbest
  Else
    Update Pbest = Pi
  Recall Pbest
End while
```

The outputs attained from the hybrid learning model using the interactive hunt-deep CNN and WoM-deep Bi LSTM are fused. The two different fusion parameters are α and β, identified optimally by the hybridized swarm optimization. Hybridized swarm optimization holds the character of two different swarms. Initially, the path is the most significant phase in determining the optimal solution. Here, the optimal solution is the fusion parameters during the exploration, which is the training process, and various solutions are obtained. The optimal solution is determined with the assistance of the fish's seeking, attack prevention, following, and waiting behaviors.

III. RESULTS AND DISCUSSION

The efficiency of the hybrid optimum learning model and other conventional methods was determined in predicting heart diseases using the datasets in [22] and [23].

A. Experimental Setup

The implementation of a hybrid optimum learning model was carried out in MATLAB on a PC with 8 GB RAM.

B. Performance Measures

The measures involved in the analysis of the hybrid learning model were accuracy, F-measure, sensitivity, and specificity. Accuracy is estimated by the total number of diseases correctly identified in the test sample analyzed. F-measure assesses the performance of a model on a dataset. It is used to evaluate categorization systems that categorize samples as either "positive" or "negative." Sensitivity describes the percentage of accurately identified patients categorized by the total number of affected individuals. Specificity describes the number of healthy individuals correctly identified by the total number of non-diseased individuals.

C. Dataset Description

The comprehensive heart disease dataset [22] combines independently accessible datasets according to specific features, while the heart disease dataset [23] uses 14 databases and includes 76 features.

D. Performance Analysis

1) Performance Using [22]

Table I and Figure 2 show the effectiveness of the hybrid optimum learning model depending on the training percentage and the epoch value.

TABLE I. PERFORMANCE USING [22]

Measures / training percentage	**Epochs: 100**			
	Accuracy (%)	**F-measure (%)**	**Sensitivity (%)**	**Specificity (%)**
40	92.379	92.802	92.693	93.335
50	93.718	93.957	93.902	94.250
60	95.435	95.783	95.611	96.302
70	96.740	96.978	97.035	97.158
80	97.734	97.859	98.021	97.822

2) Performance Using [23]

Table II and Figure 3 show the effectiveness of the hybrid optimum learning model depending on the percentage of training and the epoch value.

TABLE II. PERFORMANCE USING [23]

Measures/ training percentage	**Epoch 100**			
	Accuracy (%)	**F-measure (%)**	**Sensitivity (%)**	**Specificity (%)**
40	91.837	91.535	90.706	92.060
50	93.151	92.456	91.647	92.571
60	94.829	94.092	93.622	93.826
70	96.124	96.076	95.734	96.370
80	97.109	96.861	96.117	97.358

E. Comparative Analysis

The proposed hybrid learning model was compared with Hybrid Fuzzy based DT [24], multimodal IoT framework [19], MDCNN [25], DLMNN [19], IGDBN [26], CSO-CLSTM [27], HuS-based deep CNN, DHOA-based deep CNN, Hybrid social hunting-based deep CNN, deep Bi LSTM [28], WOA-based deep Bi LSTM, MPA-based deep Bi LSTM, and [29].

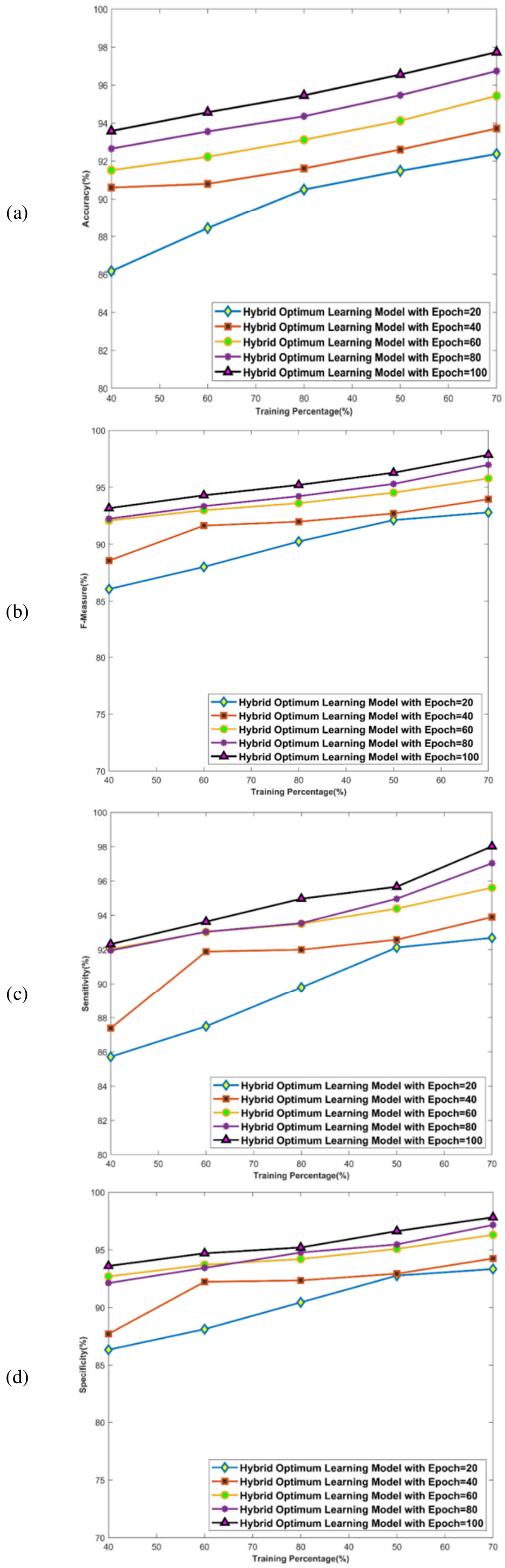

Fig. 2. Performance on [22]: (a) Accuracy, (b) F-measure, (c) Sensitivity, and (d) Specificity.

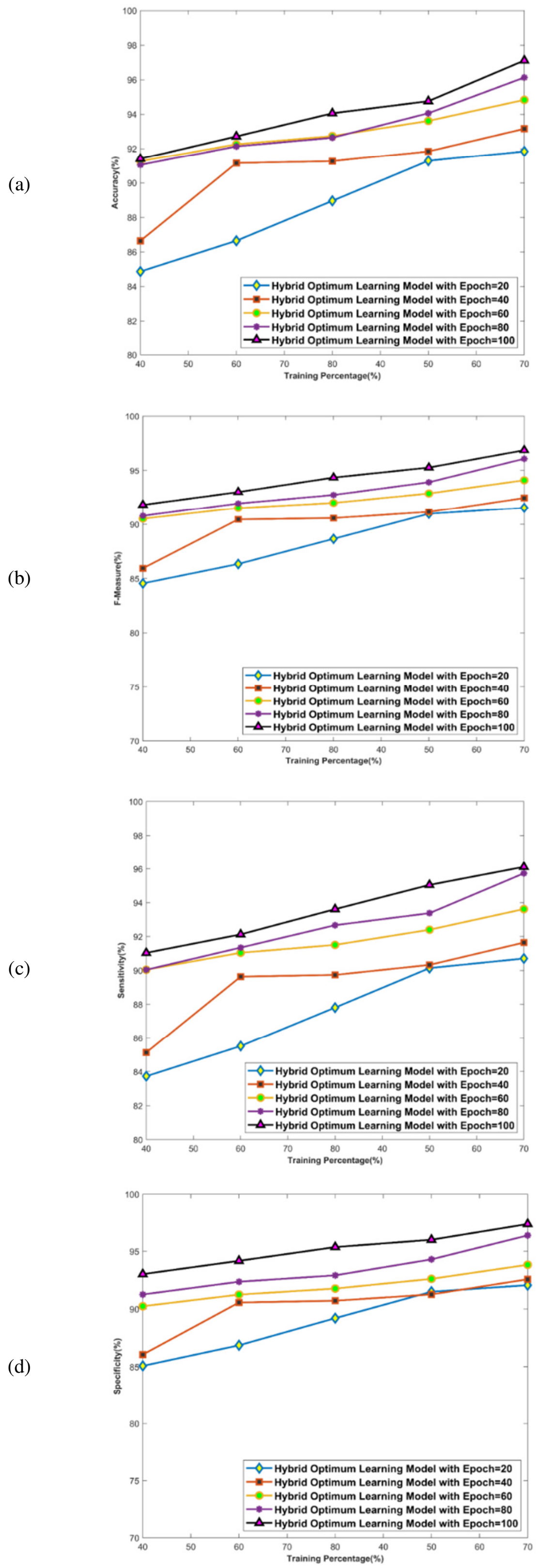

Fig. 3. Performance on [23]: (a) Accuracy, (b) F-measure, (c) Sensitivity, and (d) Specificity.

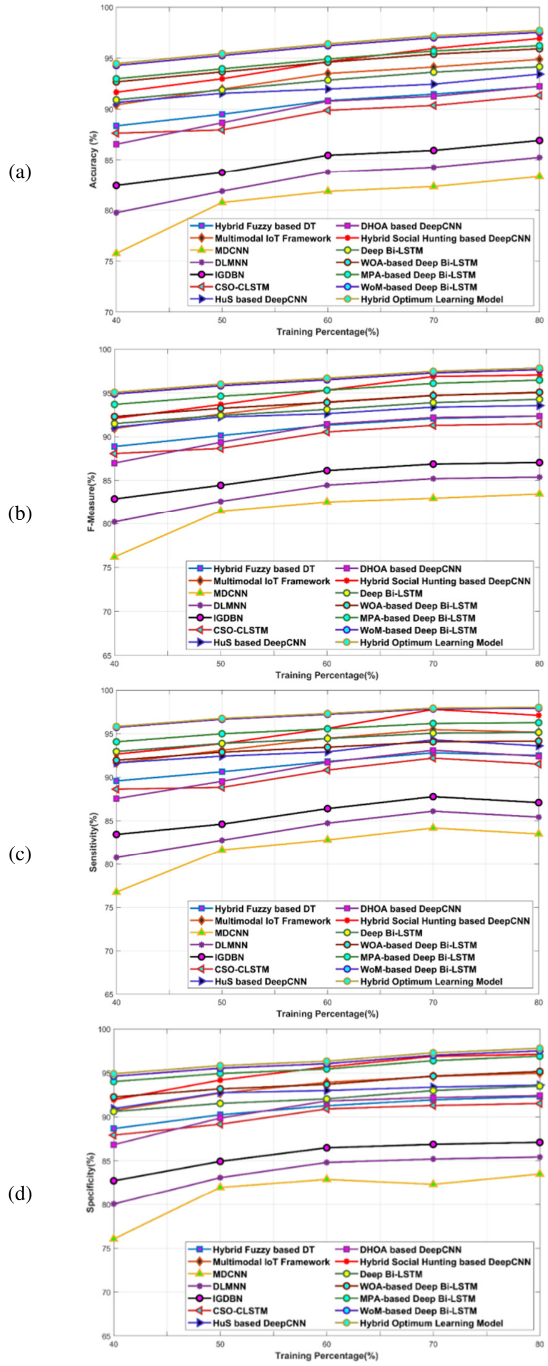

Fig. 4. Comparative analysis of the proposed hybrid and various models on [22]: (a) Accuracy, (b) F-measure, (c) Sensitivity, and (d) Specificity.

Figure 4 compares the models in [22], considering training percentages of 40 to 80, showing that the proposed model achieved 0.6% higher accuracy and F-measure than the others. Figure 5 shows the performance comparison of the proposed hybrid and previous models in [23]. The performance of the hybrid learning model was assessed in a range of training percentages (40-80%). In this case, the proposed hybrid learning model had greater accuracy, F-measure, specificity, and sensitivity by 1.42%, 1.4%, 1.8%, and 0.9%, respectively.

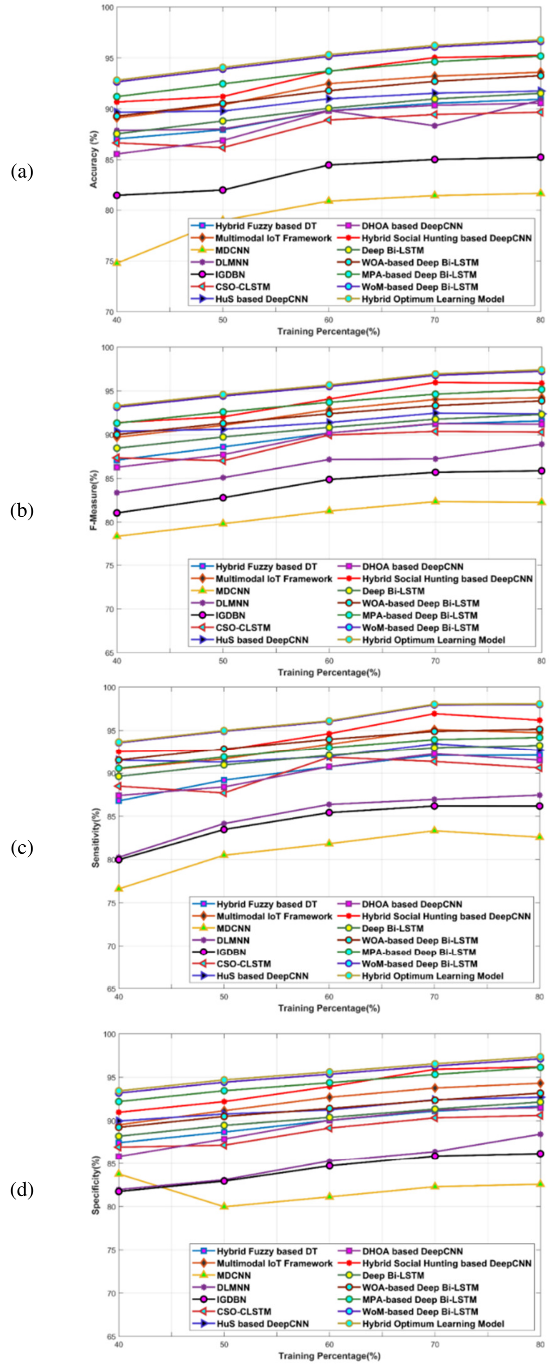

Fig. 5. Comparative analysis of the proposed hybrid and various models on [23]: (a) Accuracy, (b) F-measure, (c) Sensitivity, and (d) Specificity.

F. Comparative Discussion

Tables III and IV show that the proposed hybrid learning model attained better efficiency in predicting fusion parameters and optimizing the classifier performance.

IV. CONCLUSION

This study used a combination of advanced machine learning techniques, specifically the WoM-deep BiLSTM and interactive hunt-deep CNN classifiers, to enhance disease prediction. Two fusion parameters were introduced to optimize the performance of this hybrid model. These fusion parameters were fine-tuned using a hybridized swarm optimization approach. Furthermore, the data collected from the IoT environment were securely transmitted using a modified ECC-based Diffi-Huffman algorithm. In particular, the efficiency gains achieved through the hybridized swarm optimization are substantial, resulting in a 0.6% increase in accuracy and a 0.8% improvement in the F-measure. Furthermore, sensitivity and specificity improved by 0.4% when evaluated in [22]. For the heart disease dataset in [23], the efficiency was higher by 1.42, 1.4, 1.8, and 0.9 % in terms of accuracy, F-measure, sensitivity, and specificity.

TABLE III. COMPARATIVE PERFORMANCE USING [22]

Methods	Dataset [23] Training percentage: 80			
	Accuracy %	F-measure %	Sensitivity %	Specificity %
Hybrid fuzzy-based DT	92.223	92.350	92.511	92.317
Multimodal IoT framework	94.883	95.010	95.171	94.976
MDCNN	83.320	83.443	83.497	83.512
DLMNN	85.251	85.374	85.428	85.443
IGDBN	86.920	87.043	87.097	87.112
CSO-CLSTM	91.340	91.463	91.517	91.532
HuS- Deep CNN	93.429	93.552	93.605	93.621
DHOA-deep CNN	92.240	92.362	92.416	92.431
Hybrid social hunting based deep CNN	96.929	97.052	97.105	97.121
Deep Bi-LSTM	94.151	94.272	95.151	93.515
WOA- deep Bi-LSTM	95.915	95.078	94.154	95.165
MPA- deep Bi-LSTM	96.222	96.467	96.265	96.915
WoM- deep Bi-LSTM	97.526	97.658	97.926	97.522
Hybrid learning model	**97.716**	**97.848**	**98.021**	**97.807**

TABLE IV. COMPARATIVE PERFORMANCE USING [23]

Methods	Heart disease dataset Training percentage 80			
	Accuracy %	F-measure %	Sensitivity %	Specificity %
Hybrid fuzzy-based DT	90.935	91.562	92.090	91.662
Multimodal IoT framework	93.595	94.222	94.749	94.322
MDCNN	81.644	82.277	82.588	82.598
DLMNN	90.836	88.914	87.452	88.453
IGDBN	85.244	85.877	86.188	86.198
CSO-CLSTM	89.664	90.297	90.608	90.618
HuS- Deep CNN	91.753	92.386	92.697	92.707
DHOA- deep CNN	90.564	91.196	91.507	91.518
Hybrid social hunting based deep CNN	95.253	95.886	96.197	96.207
Deep Bi-LSTM	91.529	92.313	93.252	92.158
WOA-deep Bi-LSTM	93.256	93.864	95.152	93.185
MPA- deep Bi-LSTM	95.184	95.174	94.188	96.148
WoM- deep Bi-LSTM	96.625	97.247	97.992	97.126
Hybrid learning model	**96.789**	**97.411**	**98.073**	**97.371**

The hybrid optimal learning model can also be used to anticipate disease before it occurs. Recognizing infections earlier allows for the use of appropriate treatments to reduce their severity. This study may face challenges in scaling to real-time applications, which requires further investigation and optimization to meet the requirements of timely disease prediction in dynamic clinical environments. Future research should explore the integration of additional classifiers and advanced data collection techniques to further enhance the reliability and real-time performance of disease prediction, ensuring early recognition and treatment of diseases.

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