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Deep Neural Network and Predator Crow Optimization-Based Intelligent Healthcare System for Predicting Cardiac Diseases

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Abstract: Cardiovascular diseases (CVD) are amongst the leading causes of death worldwide. The Internet of Things (IoT) is an emerging technology that enables the healthcare system to identify cardiovascular diseases. In this article, a novel cardiovascular disease prediction framework combining Predator Crow Optimization (PCO) and Deep Neural Network (DNN) is designed. In the proposed PCO-DNN framework, DNN is used to predict cardiac disease, and the PCO is utilized to optimize the DNN parameters, thereby maximizing the prediction performances. The proposed framework aims to predict and classify cardiovascular diseases accurately. Further, an intensive comparative analysis is performed to validate the obtained results with the existing classification models. The results show that the proposed framework achieves an accuracy of 96.6665%, a precision of 97.5256%, a recall of 97.0953%, and an F1-measure of 96.4242% and can outperform the existing CVD predictors.

Keywords: smart healthcare system; cardiovascular disease; Deep Neural Network; high blood pressure; Predator Crow Optimization

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1. Introduction

Cardiovascular diseases or diseases of the heart and circulatory system are a leading cause of severe illness and death worldwide. Diseases of the cardiovascular system manifest as cardiovascular events, which are a disruption of the circulatory system presenting as myocardial infarction, stroke, dizziness, etc. [1]. A number of risk factors, such as diabetes, high blood pressure, and high cholesterol, have been identified to contribute to cardiovascular diseases. In spite of technological advancements, it is challenging to detect early stage cardiac diseases in most settings [2]. The occurrence of a cardiac disease has the potential to drastically limit a person's productivity and well-being [3]. Cardiac arrest can manifest as sudden collapse of the patients. Medical tools, such as defibrillators, help provide a high-energy shock to the heart during cardiac arrest aiding the reactivation of the normal heart activity and recovery of the patients [4]. The World Health Organization (WHO) reports that chronic diseases have significantly increased in wealthy nations in the past few decades. This has been mainly attributed to lifestyle diseases and the ageing population. Comorbidity, or multiple illnesses in the same person, is another crucial factor complicating the management of such patients [5–8]. Comorbid conditions in the elderly are a matter of greater concern [9]. Newer technology has been increasingly utilized in the prevention and management of such diseases in recent decades.

Modern medical milestones are represented by 5G systems, internet services, artificial intelligence (AI), microelectronics, big data, cloud computing (CC), and smart bioengineering. These techniques are employed at every stage of sophisticated medicine [4]. The Internet of Things (IoT)', given its capacity to assist in solving diverse health-related problems in a highly efficient manner, has attracted the attention of scientists desirous of contributing to this domain [10]. Examples of intelligent healthcare that can profit from the IoT include elderly care, remote patient monitoring, wellness treatment, chronic disease control, and supported accommodation [9,11]. Medical devices with sensors are referred to as smart gadgets. The IoT has been shown to lower equipment costs and increase human lifespans with the help of healthcare providers [12]. The IoT enables more effective scheduling of scarce resources, facilitating the monitoring of a greater number of patients [9]. Remote healthcare monitoring can be used to predict and identify the condition early, and people's clinical records can be stored within the database for future use. With the use of such technology, patients can have easy and timely access to their health records [5].

When required, patients can monitor their health using portable or wearable devices. They can utilize remote facilities to control their homes and as virtual aids to obtain medical advice. Experts in medicine believe that highly developed clinical decision-support tools could be used to guide and improve medical testing. An innovative concept called the "Internet of Medical Things" (IoMT) has emerged due to the widespread acceptance and implementation of modern clinical instruments and support hardware for healthcare providers [13]. The healthcare industry and the prevalence of IoT-enabled medical devices have undergone significant transformations, offering new opportunities for healthcare professionals and researchers [11]. These advancements allow investigators to monitor a user's activities through various means, including portable sensors, ingestible devices, and embedded sensors, as well as tracking smartphone usage and gadget patterns. With the wealth of data collected, modern technologies like artificial intelligence (AI) and deep learning (DL) can be harnessed to gain insights into an individual's health status [1]. Machine learning (ML) techniques, particularly deep learning, have shown promise in population-based research for assessing cardiovascular risk, predicting cardiac events, and identifying valuable biomarkers such as ECG signals [14].

Although several machine learning-based methods for predicting and diagnosing cardiac diseases have emerged in recent times, there are notable limitations. Existing intelligent frameworks often struggle to effectively utilize data from multiple sources, especially when dealing with high-dimensional datasets [15]. Furthermore, traditional algorithms typically select features from a dataset and compute their overall significance, which does not always lead to improved accuracy in diagnosing cardiac diseases. Therefore, there is a pressing need to address these challenges and enhance the accuracy and computational efficiency of cardiac disease diagnosis systems, which serves as the primary motivation for this research.

The Predator Crow algorithm-based DNN classifier is a hybrid optimization technique. This study introduces the IoT-based identification of cardiovascular illnesses utilizing patient ECG information. The suggested Predator Crow technique is used to update the weights of the DNN classifier, which is applied to the classification of cardiovascular diseases. The input signal's mean, variance, standard deviation, kurtosis, and skewness are all collected to complete the classification process effectively. The results of this study also provide a comprehensive description of the proposed paradigm, enabling the verification of its efficacy. Additionally, a thorough evaluation of the effectiveness of traditional categorization systems is offered to assess the superiority of the suggested approach to cardiovascular disease identification. The proposed methods provide correct accuracy and decrease computational time. The significant contribution of this research is summarized as follows:

- The study focuses on designing a hybrid system for predicting cardiovascular diseases, which combines PCO (Predator Crow Optimization) with DNN (Deep Neural Networks) to create an intelligent healthcare solution.

- Initially, an ECG (Electrocardiogram) signal database is collected and used as input for the cardiovascular disease prediction system.
- The system employs a band-pass filter for data preprocessing and feature extraction. This step helps clean and prepare the data for further analysis.
- The core of the system is an integrated PCO-DNN framework, where DNN is responsible for predicting cardiovascular diseases, and PCO optimizes the DNN parameters to enhance prediction performance. PCO is a nature-inspired optimization algorithm inspired by the hunting behaviors of crows.
- The performance of the Predator Crow-DNN model is compared to that of conventional models, using metrics such as accuracy, precision, recall, and F-measure. This comparative analysis provides insights into the effectiveness of the proposed hybrid system in predicting cardiovascular diseases.

These points provide an overview of the approach and methodology used in the study for cardiovascular disease prediction and the evaluation of the proposed model's performance against traditional models.

2. Literature Survey

The field of predicting cardiovascular diseases has seen various techniques and models developed over time, each with its own set of limitations. The need for the suggested model arises from these limitations, and it aims to address these issues. In the medical domain, knowledge is derived from data and experiences of medical professionals. The human body is highly complex and susceptible to various factors, making modeling its functions and dysfunctions a challenging and time-consuming process.

Machine learning techniques have become instrumental in using medical data for diagnosing and forecasting various illnesses, playing a vital role in e-health systems. For instance, in a previous study [4], Mansour et al. introduced the Crow Search Optimization-based Cascaded Long Short-Term Memory (CSO-CLSTM) framework, which leverages AI and convergence methodologies to identify illnesses. The CSO-CLSTM model demonstrated strong classification rates and specificity. However, it faced challenges related to the complexity and intricacy of the proposed system.

Another approach, as seen in the work of Kumar and Gandhi [3], involved a scaled three-tier system for managing a large volume of wearable sensor data. Tier 1 focused on data collected from IoT wearable sensor devices, Tier 2 employed Apache HBase to store data from integrated IoT devices within the cloud, and Tier 3 used Apache Mahout to create a probabilistic linear extrapolation heart disease prediction model. However, this approach could be computationally demanding due to its sequential nature.

These examples highlight the ongoing efforts to improve disease prediction models, and our suggested model aims to contribute to this area by addressing specific limitations and providing a novel approach to predicting cardiovascular diseases. Mohan et al. [2] used machine learning techniques to design a novel strategy for detecting essential traits and enhancing cardiovascular illness prediction accuracy. The prediction model is developed with different combinations of attributes and well-known methods to obtain higher performance. The revolutionary techniques proposed here are simple and efficient, improving heart disease prediction while lowering costs. Nevertheless, feature selection methods are needed to obtain a broader view of the critical information to enhance the accuracy of heart disease prediction.

Dami and Yahaghizadeh et al. [1] created a deep learning strategy using 5 min (ECG) recordings. They retrieved the time–frequency characteristics of electrocardiogram data to predict vascular catastrophes a few days before the occurrence. The Long Short-Term Memory (LSTM) neural net was used to investigate the prospect of learning long-term connections in the ability to detect and prevent these events swiftly. The fact that there must be defined criteria for experimentation and evaluation since the topic is unique, however, serves as one of the research's shortcomings.

Basheer et al. [5] developed a hybrid fuzzy-based tree-based method for the early diagnosis of cardiac diseases using a constant and remote patient monitoring program. The mixed fuzzy-based decision tree method successfully detects cardiac disorders compared to previous classification methods. However, there is no fixed system or set of IoT implementation standards. It cannot be utilized everywhere and needs to offer adequate solutions to the issues. Kaur et al. [6] developed a healthcare system based on the IoT and a Random Forest classifier. The developed approach improves interactivity between patients and doctors. However, developing and deploying a healthcare system via cell phones involves several challenges. A deep learning-based IoT health surveillance system has been introduced by Wu et al. recently [7]. This method might help identify dangerous disorders amongst athletes such as tumors, heart issues, cancers, etc.

On the other hand, the classifier that was used to build the model can result in overfitting, complexity, and high processing costs. For example, an Internet of Things peripheral heart rate monitoring intelligent sports wristband system was created by Xiao et al. [8] to track changes in patient's heart rate while engaging in athletics. The physiological parameters in the constructed model focus primarily on the heart rate. Critical metrics, such as blood pressure, need to be addressed, which is significant or a flaw in the method. Table 1 summarizes predicting cardiovascular disease using a Predator Crow Optimization-tuned deep neural network for an intelligent healthcare system.

Table 1. Summary of surveys from the literature.

Refs.	Technique	Findings	Advantages	Disadvantages
[1]	Long Short-Term Memory (LSTM) neural net	Mean accuracy	The accuracy is good	Non-continuous feasible monitoring
[2]	Revolutionary methods	Accuracy	The cost is low	Increases computational time
[3]	Scaled three-tier system	Sensitivity specificity	The technique is simple	Difficult to interrupt
[4]	Crow Search Optimization-based Cascaded Long Short-Term Memory (CSO–CLSTM) framework	Accuracy	High sensitivity	Low recall
[5]	Hybrid fuzzy-based tree-based method	Sensitivity, specificity, and accuracy	Recall is higher	When using large datasets, the training time is extended
[6]	Random Forest classifier	Maximum accuracy	F1-score is higher	Difficult to interrupt
[7]	Deep learning-based IoT	Precision and F1	Decreases computational time	The weights of the variables are not constant
[8]	The smart sports wristband system	Accuracy	Higher accuracy	Low-dimensional data
[16]	MSSO with Random Forest model	Accuracy and efficiency	Greater accuracy, and high classification efficiency	Depends on the database's quality
[17]	Correlation-based feature selection and hyperparameter optimization	Accuracy, AUC	Increased classification accuracy	Limitation to transferability, and generalizability
[18]	Smart healthcare system based on Bi-LSTM	Sensitivity, specificity, accuracy, and f-measure	Ability to control sequential healthcare database	High computational time and demands more resources
[19]	Cluster-based BiLSTM	F-measure, sensitivity, and accuracy	Robustness and transferability	Instability
[20]	Computational method based on CNN	Accuracy	Enhanced accuracy	Depends on the consistency and quality of the input images

Cenitta et al. [16] presented an integrated cardiac disease prediction model using the modified squirrel search optimization (MSSO) and the machine learning model. This approach incorporated the MSSO with the Random Forest algorithm for optimal feature extraction and selection. This helps minimize the number of attributes and records in the classification process. This model was evaluated with the ischemic heart disease database, and the implementation results demonstrate that the designed model attained greater efficiency in disease identification. However, the model's reliability depends on the image dataset's quality. Reddy et al. [17] designed an effective heart disease identification model using the optimization and principal components. This method concentrates on feature extraction and selection. Initially, the feature extraction was performed to track the principal elements, and then the feature selection was carried out to choose the optimal principal element in the heart database. Further, an ensemble classification module and hyperparameter optimization was designed for classification purpose. Optimization integration enhances the accuracy and area under the curve (AUC) of the system. However, this method is restricted to generalizability and transferability.

Nancy et al. [18] presented a smart healthcare framework using the bidirectional-LSTM (Bi-LSTM) to predict heart diseases accurately. This method utilizes the capacity of the LSTM to control and regulate the sequential time-series healthcare database. The simulation analysis illustrates that the designed framework gained 88.86% of prediction accuracy, 88.8% of sensitivity, and 88.86% of specificity. However, this method is computationally intensive and requires more resources.

Dileep et al. [19] developed cluster-based BiLSTM to identify and classify heart diseases. This model was evaluated with the publicly available UCI heart disorder base. The experimental outcomes are determined and manifested with the typical classifier models like K-nearest neighbor, support vector machine, logistic regression, etc. The effectiveness of the developed model is tested in terms of accuracy, f-measure, and sensitivity. However, using the clustering algorithm produces various outcomes each time it is applied to the same database.

Sharma et al. [20] introduced an innovative computational framework for accurately identifying heart diseases. This framework utilizes the convolutional neural network (CNN) to categorize heart disease images from the normal classes. This proposed model was modeled in the TensorFlow platform and attained approximately 96% accuracy. However, the outcomes of the CNN model depend on the consistency and quality of the input images, such as noise, imaging techniques, image resolution, etc.

Challenges

- Heartbeat and Pulse Rate Monitoring: The use of a 650 nm green LED as a light source for pulse rate monitoring is common, allowing light to penetrate various tissues. However, the output current from photosensitive elements is typically low, making them susceptible to external electromagnetic interference. Additionally, the electrical signal generated by photoelectric conversion may be weak, which can pose challenges in capturing accurate pulse information [8].
- Data Preprocessing and Feature Extraction: To ensure the quality of telemedicine data and avoid data duplication, extracting meaningful features from raw data using deep learning and machine learning algorithms is essential. This process helps filter out duplicate, noisy, and inaccurate data before storage in remote cloud data centers, thus optimizing resource utilization and avoiding potential negative health-related consequences [7].
- Real-Time Health Surveillance: Contemporary health surveillance systems rely on real-time analytics to provide critical information swiftly and improve response times. However, challenges may arise due to unstable network connections and inconsistent data flows from remote sensors, potentially affecting the efficiency of these systems [7].
- Deep Learning Model Complexity: Increasing the number of hidden units in a deep learning model can lead to improved accuracy in training and testing procedures.

However, it also introduces challenges such as higher processing costs, increased model complexity, and the risk of vanishing gradient problems, which can hinder the training process [7].
- These points highlight some of the technical and practical considerations in health monitoring and data analysis, particularly in remote or telemedicine applications. Addressing these challenges is crucial for enhancing the accuracy and reliability of health-related systems and ensuring they deliver meaningful results.

3. Proposed PCO-DNN Approach for Cardiovascular Disease Prediction

A noticeable increase in wearable technology monitoring patient health, fitness, and activities has occurred. This has long-term effects on healthcare, medical services, and the storing private patient information. This approach also gives more information regarding the physical evaluation and daily agenda. During the health monitoring phase, wearable IoT devices are connected to the body to assess a range of health indicators, including heart rate, skin temperature, blood circulation, breathing rates, muscle aches, and sugar levels. Using the data obtained by the IoT portable tech and stored in a clinical database, critical actions are promptly taken when a participant's overall health shows signs of deterioration [21].

The proposed deep neural network and Predator Crow algorithm are two different approaches for predicting cardiac diseases. While the deep neural network is an artificial neural network that can learn and model complex relationships between inputs and outputs, the Predator Crow algorithm is a nature-inspired optimization algorithm based on the hunting behavior of predator crows. The major benefits of utilizing the DNN framework include, the DNN provides remarkable performances on standard machine learning tasks such as image recognition, natural language processing, etc. Thus, the DNN offers remarkable performances in cardiac disease classification by identifying the complex patterns and interrelationships between normal and abnormal images. Moreover, the availability of pre-trained models in DNN makes the training process faster and reduces the computational time and resources effectively. In addition, the recent neural network structures are complex and often create false positives and false negatives in the disease classifications and they require large data resources for training. However, the simple structure of DNN does not require large databases and has the tendency to generalize for unseen data. These advantages of the DNN make it a more reliable choice for disease prediction. On the other hand, the PCO approach is a nature-inspired optimization technique, which mimics a crow's hunting characteristics. It combines the exploitation and exploration methods to search the parameter space efficiently. This approach has the capability to explore new search space while exploiting promising areas. Moreover, it finds the global optimum rather than the local optima and avoids convergence to suboptimal solutions. Unlike other optimization techniques that rely on gradient data, the PCO does not require objective function derivatives. Thus, this optimization algorithm is more suitable for optimization of neural network parameters. Moreover, the PCO approach has fewer tuning parameters than other optimization techniques. This feature of PCO optimization reduces the model complexity and eliminates the need for fine-tuning. These advantages of the PCO make it more effective for optimizing the neural network tuning parameters.

The main difference between these two approaches lies in their underlying methodology. The deep neural network uses a supervised learning approach to train the network with a large dataset of labeled examples. At the same time, the Predator Crow algorithm is an optimization algorithm that aims to find the optimal set of parameters that maximize or minimize a given objective function. The sensor readings of patients [22] are used in this research to present a deep learning model-based technique again for diagnosing cardiac illnesses. The doctor in the sink node takes the ECG signals to process them in such a way as to predict the cardiovascular diseases of patients automatically.

The tuning of DNN parameters assists the system in attaining an enhanced performance in predicting cardiovascular diseases. Figure 1 shows a graphical representation depiction of the suggested seizure forecasting model. Generally, the data are collected using the BSN, which is processed to detect the presence of cardiovascular diseases. This research analyzes the cardiac vascular dataset obtained by the IoT system. The raw ECG signal may include certain 'noise' or artifacts due to chest movement during breathing, patient movements, inadequate skin preparation, etc. These artifacts in the ECG signal affect the edge function and hence change the shape of the waveform. Therefore, the ECG signal needs to be pre-processed precisely for further action, such as the extraction of features and the classification of the signal by using a DNN classifier. Digital filters are significant in analyzing the low-frequency components in ECG signals. Some biomedical signals possess low frequency, and removing baseline wander (BLW) and power line interference is an essential step at the pre-processing stage of the ECG. Thus, the proposed research uses the band-pass filter to remove unwanted artifacts in the ECG signal [23].

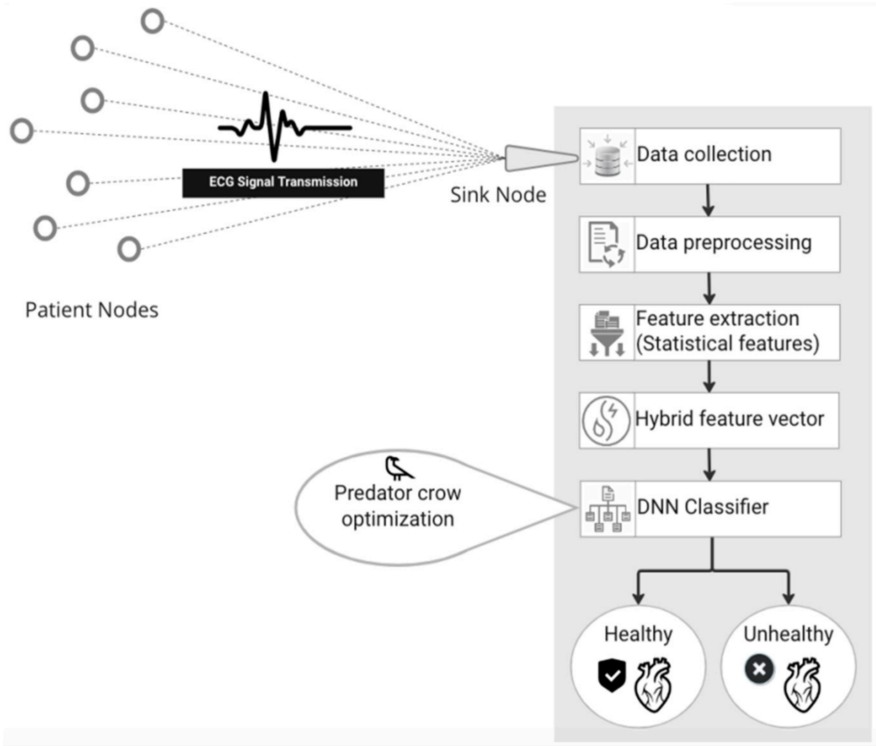


Figure 1. Architecture of the PCO-DNN framework.

Extracting characteristics from the pre-processed input ECG data is a crucial next step in the suggested cardiovascular disease detection phase. The gray-level co-occurrence matrix (GLCM) feature extraction strategy determines the feature vector from a regular vector. A matrix that displays various combinations of grey levels that can be found in a picture is known as a "gray-level co-occurrence matrix" (GLCM). The various areas in the images could be distinguished due to the textural elements that the GLCM derived from the images. It involves selecting the features or data that are the most significant to execute the detection process. The statistical features are the most important for the proposed cardiovascular disease detection strategy since they reveal even the most minor changes in the ECG signal, improving classification accuracy [24]. The mean, variance, and standard deviation can capture changes in the signal's average, spread, and distribution. Kurtosis and skewness can capture changes in the shape and symmetry of the distribution. While these measures may not capture all possible changes in the signal, they can still help identify patterns and trends in the data. The mean, variance, standard deviation, skewness, and kurtosis are the statistical properties that support the validity of the results. Further, to improve cardiac disease detection, it is necessary to extract the time and frequency-based features. In the proposed work, a Fast Fourier Transform (FFT) was employed for tracking and extracting the time and frequency-based features. The statistical and time-frequency feature analysis enables advanced and precise disease prediction. The accuracy of the suggested primary heart disease feasibility is improved by carefully choosing essential features. The DNN network uses the extracted features as an input to classify the ECG signal as normal or abnormal.

3.1. Procedure for PCO-Tuned DNN

Machine learning's DNN subfield is motivated by the operations and procedures of the human mind. The DNN model is chosen above conventional machine learning methods for various reasons. First, standard learning algorithms only employ a single stacking processing layer, which cannot handle complex natural data with high nonlinearity. Second, to select the best data for precise prediction, standard algorithms for machine learning require technical or human skills [7]. Human skills deal with people, whereas technical skills deal with things. An instruction set known as a "learning algorithm" is used in machine learning to enable a software program to mimic how a human becomes more adept at classifying particular types of information.

The input image, output layer, and multiple hidden layers comprise the bulk of DNN models. An output connection is a transfer function that mixes the inputs. One or more weighted input connections formulate a node, additionally known as a neuron or a perceptron. After that, nodes are arranged into layers to form a network. Epoch count is regarded as a hyperparameter. It specifies how often the learning algorithm must process the complete data collection. The underlying model parameters have been updated once throughout an epoch for each sample in the training dataset. The DNN model's hidden units are crucial components and actively participate in learning. Although adding hidden layers to a model during training can improve its effectiveness, doing so has a price. That price is in the form of processing time, the complexity of the model, and the prediction accuracy [25,26]. Equation (1) can be used to formalize the DNN model as

$$q_r = f\left(G_r + \sum_{w=1}^{a} L_w \psi_w^r\right) \tag{1}$$

where q_r represents the output at the layer r, the bias value, and the layer r weight through the neuron w. The term L_w signifies the feature input and f is the nonlinear activation of the Tanh function. It can be designed using Equation (2).

$$f(x) = \frac{e^x}{1 + e^x} \tag{2}$$

Movable weights connect the synapses for each layer. The suggested technique is utilized to update the weights of the prediction model to improve the forecast accuracy of the proposed heart disease prediction module. In addition, it inherited the meal-seeking distinctive traits of both raider search agents and crow search agents.

3.2. Proposed Predator Crow Algorithm in DNN

The proposed Predator Crow Optimization technique involves the tuning of the weights of the DNN classifier in such a way as to perform an accurate prediction of cardiovascular diseases. To provide a better solution for the optimization problem, the algorithm adopts the hunt characteristics of the raiding iteration of the algorithm [27] and the memory characteristics of the crow search agent [28]. Predator Crow Optimization (PCO) is a nature-inspired optimization algorithm that emulates the hunting behavior of predator crows. Compared to other popular optimization algorithms, such as the genetic algorithm (GA), particle swarm optimization (PSO), and ant colony optimization (ACO), PCO offers several advantages. On the other hand, GA, PSO, and ACO are popular optimization algorithms, and PCO offers distinct benefits in efficiency, robustness, simplicity, convergence, and scalability. These advantages make PCO a promising optimization algorithm for solving complex real-world problems. The following are the steps of the Predator Crow Optimization algorithm:

Step 1: Population Initialization

The raiding search agents' population is set up. In the initial trial, the initial answer is dispersed uniformly throughout the search area as

$$S_0 = S_{\min} + rand(S_{\max} - S_{\min}) \tag{3}$$

where $S_{\min}$ and $S_{\max}$ are the variables' lower and upper bounds, and $rand$ denotes the random variable in the range between 0 and 1. The raiding search agents' population is formulated as

$$S^{rs}_{s,t}; (1 \leq s \leq \tau) \tag{4}$$

where τ represents the overall number of raiding search agents, and t denotes the search area's size. The prey population is specified in the same way as the search agents, and it is represented as $S^{prey}_{s,t}$.

Step 2: Process States of Raiding Search Agents

The three stages of the optimization problem are unit speed ratio, high-speed ratio, and then low flow ratio. Each phase has a specific iteration period, determined by the raiding search agents' and prey's velocity.

Phase 1: High-Velocity Ratio

The raiding search agent moves slower than the prey during this phase, which happens early in the repetition when the exploring location is crucial. The best strategy for the raiding search agent is to remain stationary throughout this time, which may be expressed mathematically as

$$\left.\begin{array}{l} While \quad Q < \frac{1}{3}Q_{\max} \\ S_{size,i} = \overrightarrow{Y_A} \otimes \left(\overrightarrow{J_i^{rs}} - \overrightarrow{Y_A} \otimes \overrightarrow{J_i^{prey}}\right); \quad i = 1, 2, \ldots, s \\ \overrightarrow{J_i^{prey}} = \overrightarrow{J_i^{prey}} + C.\overrightarrow{Y} \otimes S_{size,i} \end{array}\right\} \tag{5}$$

where $S_{size,i}$ represents scalar, Y_A is a vector of random numbers corresponding with Brownian movement, C is a constant with the value of 0.5, the representation $\otimes$ demonstrates entry-wise multiplication, Y is a random number changing between 0 and 1, Q represents the present iteration, and $Q_{\max}$ represents the extreme iteration. This is the first half of the cycle, and it entails a faster rate of exploration.

Phase 2: Unit Velocity Ratio

During the optimization process, when the search agent and the prey have similar velocities while actively pursuing their respective target, there comes a point at roughly the halfway mark of the process. At this stage, the focus shifts from exploration to exploitation. In this phase, approximately half of the population engages in the discovery phase, while the other half takes part in the exploitation phase.

This transition from exploration to exploitation can be expressed mathematically to formalize how the population is divided and how these agents work during this specific phase of the optimization process. The specific mathematical expressions and equations may depend on the optimization algorithm or method being used in the context. This can be expressed mathematically as follows:

$$\left.\begin{array}{l} While \quad \frac{1}{3}Q_{\max} < Q < \frac{2}{3}Q_{\max} \\ S_{size,i} = \overrightarrow{Y_R} \otimes \left(\overrightarrow{J_i^{rs}} - \overrightarrow{Y_R} \otimes \overrightarrow{J_i^{prey}}\right); \quad i = 1, 2, \ldots, s/2 \\ \overrightarrow{J_i^{prey}} = \overrightarrow{J_i^{prey}} + C.\overrightarrow{Y} \otimes S_{size,i} \end{array}\right\} \tag{6}$$

where $S_{size,i}$ represents scalar, and Y_R is a vector of random numbers whose distribution is determined by the Levy distribution. The operation for the second half of the population is written as follows:

$$\left.\begin{array}{l} While \quad \frac{1}{3}Q_{\max} < Q < \frac{2}{3}Q_{\max} \\ S_{size,i} = \vec{Y}_A \otimes \left(\vec{Y}_A \otimes \vec{J}_i^{ps} - \vec{J}_i^{prey} \right); \quad i = s/2, \ldots, s \\ \vec{J}_i^{prey} = \vec{J}_i^{prey} + C.M \otimes S_{size,i} \end{array}\right\} \tag{7}$$

$$M = \left(1 - \frac{Q}{Q_{\max}}\right)^{\left(2\frac{Q}{Q_{\max}}\right)} \tag{8}$$

where $S_{size,i}$ represents scalar, and Y_A is a vector of random numbers; M is a controllable parameter that helps regulate the raiding search agent's speed.

Phase 3: Low-Velocity Ratio

At this stage, the raiding search agent moves more quickly than the prey, which suggests a strong capacity for exploitation. The following is a description of this stage:

$$\left.\begin{array}{l} While\ Q > \frac{2}{3}Q_{\max} \\ S_{size,i} = \vec{Y}_R \otimes \left(\vec{Y}_R \otimes \vec{J}_i^{ps} - \vec{J}_i^{prey} \right); \quad i = 1, 2, \ldots, s \\ \vec{J}_i^{prey} = \vec{J}_i^{prey} + C.M \otimes S_{size,i} \end{array}\right\} \tag{9}$$

where $S_{size,i}$ represents scalar, and Y_R is a vector of random numbers. This phase aids raiding search agents in triggering the Levy tactic, which causes the prey to adjust its position.

Step 3: Update of Position

The raiding search agents create long hops over many dimensions to locate the prey. This longer hop prevents the algorithm from becoming stuck in a locally optimal solution. As a result, the prey's location can be updated as follows:

$$J_{i+1}^{prey} = J_i^{prey} + M\left(\vec{S}_{\min}^{rs} + \vec{Y} \otimes \vec{S}_{\max}^{rs} - \vec{S}_{\min}^{rs} \right) \otimes \vec{H} \tag{10}$$

This is the usual equation for updating the prey's position using raiding search agents, where $\vec{H}$ denotes a binary vector with arrays of ones and zeros. The convergence criterion may not be ensured if only the first stage of the procedure is completed, and the other two steps are skipped. Raiding search agents are additionally not allowed to catch the fittest prey, contributing to improved position updating for the best outcome. As a result, the raiding search agents' characteristics must be improved, which is why the crow search agents' features are included in the suggested optimization system. Regardless of size, the crow search agents are clever agents with giant brains. They have heightened self-awareness and the ability to construct tools. Even after several months, they recall the faces and food locations. Crows are known as effective search agents because they can establish flocks, remember where food has been placed, follow one another to procure it, and watch over the young. Consider how a crow search agent e follows a fresh crow search agent to set up a new location in the search area j from a randomly chosen flock of crow search agents [25]. The crow search agent's new position i is stated as follows:

$$J_{e,i+1}^{cs} = J_{e,i}^{cs} + rand \times FL_{e,i} \times \left(mem_{j,i} - J_{e,i}^{cs} \right) \tag{11}$$

where $J^{cs}_{e,i}$ represents the e^{th} crow search agent position at i^{th} iteration, $mem_{j,i}$ denotes the memory status of the j^{th} crow search agent, *rand* denotes a random number that varies between 0 and 1, and $FL_{e,i}$ is the flight length. Finally, the hybridized expression combining the characteristic features of both the raiding search agent and crow search agent (J^{PC}_{i+1}) with equal importance is obtained as

$$J^{PC}_{i+1} = 0.5 J^{rs}_{i+1} + 0.5 J^{cs}_{i+1} \tag{12}$$

$$J^{PC}_{i+1} = 0.5\left[J^{prey}_{i} + M\left(\vec{S}^{rs}_{\min} + \vec{Y} \otimes \vec{S}^{rs}_{\max} - \vec{S}^{rs}_{\min}\right) \otimes \vec{H}\right] + 0.5\left[J^{cs}_{e,i} + rand \times FL_{e,i} \times \left(mem_{j,i} - J^{cs}_{e,i}\right)\right] \tag{13}$$

$$J^{PC}_{i+1} = \frac{1}{2}\left\{J^{prey}_{i} + M\left(\vec{S}^{rs}_{\min} + \vec{Y} \otimes \vec{S}^{rs}_{\max} - \vec{S}^{rs}_{\min}\right) \otimes \vec{H} + J^{cs}_{e,i} + rand \times FL_{e,i} \times \left(mem_{j,i} - J^{cs}_{e,i}\right)\right\} \tag{14}$$

The typical equation of the Predator Crow Optimization method, which includes the properties of the raiding search agent and crow search agent, is given above.

Step 4: Fitness Determination

The ability of all predator crow search agents to recollect the location where superior foraging occurs determines their fitness. Therefore, the fitness of each iteration is compared to the current fitness, and if a search agent with higher fitness is found, it is replaced with the existing one.

Step 5: Termination Condition

Until the terminating condition has been satisfied, the procedure outlined above is repeated; after that, the algorithm terminates. This approach involves determining the DNN's weights to predict cardiovascular diseases accurately. The pseudocode for the suggested optimization technique is shown in Algorithm 1. Figure 2 presents the flowchart of the designed model.

Algorithm 1: Pseudocode of the proposed Predator Crow Optimization algorithm

Input: $S^{rs}_{s,t};\ (1 \le s \le \tau)$
Initialize the population of predator crow search agents
Initialize maximum iteration $Q_{\max}$
Evaluate fitness function for all predator crow search agents
Process states of raiding search agents
  High-velocity ratio
    If $Q < \frac{1}{3} Q_{\max}$
        Unit velocity ratio
          Update position based on Equation (5)
    Else if $\frac{1}{3} Q_{\max} < Q < \frac{2}{3} Q_{\max}$
          Update position based on Equation (6) for the first half of the population
          Update position based on Equation (7) for the next half of the population
          Low-velocity ratio
    Else if $Q > \frac{2}{3} Q_{\max}$
          Update position based on Equation (9)
      Update memory
      Update position based on Equation (11)
      Evaluate the fitness of all predator crow search agents
      If $fitness_{old} < fitness_{new}$
  Replace the old solution with the new solution
  Return J^{PC}_{i+1}

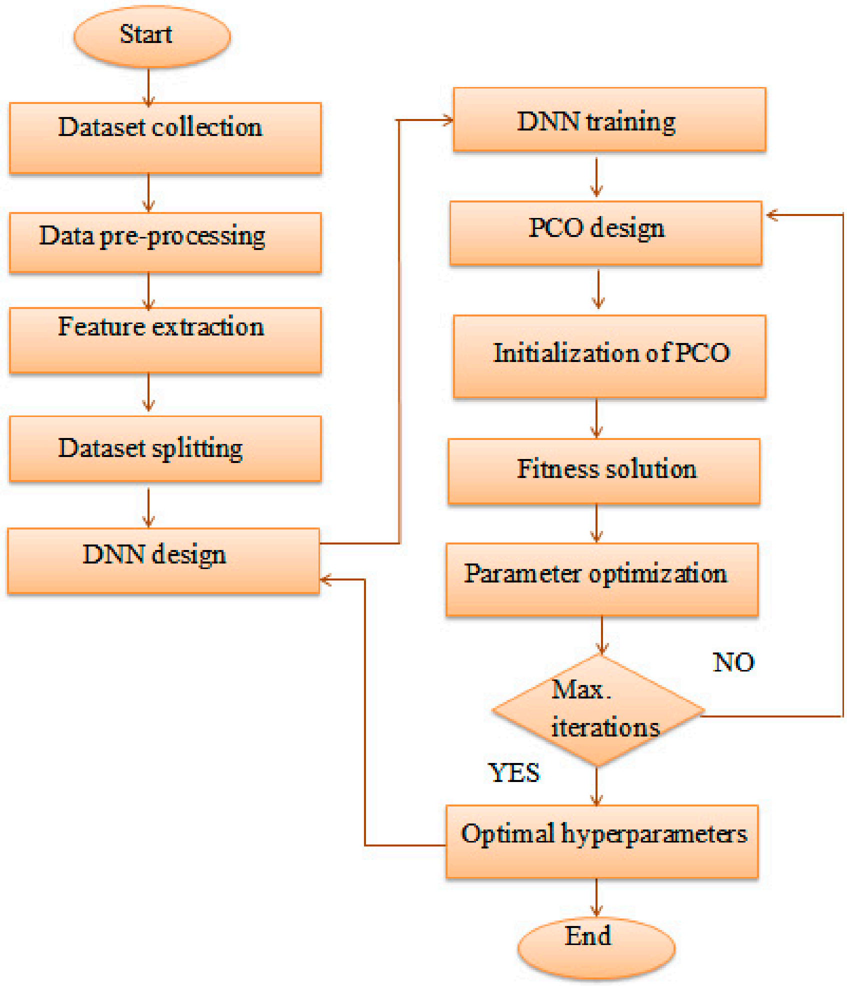


Figure 2. Flowchart of the proposed work.

4. Results and Discussion

4.1. Experiment Setup

The experiment was conducted using Python programming language, installed on a 64-bit Windows 10 computer with 32 GB of RAM. The experiment is conducted for a population size of 100.

4.2. Database Description

The CVD database is the dataset used in the proposed cardiovascular disease prediction module. To evaluate the proposed framework, five different publicly available databases are used, namely, Heart Disease UCI [29], Cardiovascular Disease Dataset (CDD), Cleveland Clinic Heart Disease (CCHD), Hungarian Institute of Cardiology Heart Disease (HICHD), and Swiss Heart Disease (SHD). These databases are collected from the Kaggle site. The databases contain a total of 76 attributes, but the analysis makes use of only 14 specific features. These 14 features are sex, cholesterol (chol), exercise-induced angina (exang), age, thalassemia type (thal), chest pain type (cp), diagnosis of heart disease (num), resting electrocardiographic results (rstecg), fasting blood sugar (fbs), ST depression induced by exercise relative to rest (oldpeak), and slope of the peak exercise ST segment (slope). Among these features, the target parameter "target" is used to represent the presence of heart disease. It can take values ranging from 0 to 4, but for practical purposes, it is often simplified into a binary classification problem, where 0 represents the absence of heart disease, and 1 represents the presence of heart disease.

This binary representation simplifies the problem, making it easier to classify individuals into two groups: those without heart disease and those with heart disease, which is a common approach for practical healthcare applications.

In this research, various datasets have been used to evaluate the effectiveness of machine learning and deep learning models in predicting and classifying cardiovascular heart disorders. Here's a brief overview of the datasets: The UCI Heart Disease Database consists of 303 records and is a well-known resource for studying heart conditions. Cardiovascular Disease Dataset: This extensive dataset contains a substantial 70,000 instances of cardiovascular disease, making it a valuable resource for researching these conditions. Cleveland Clinic Heart Disease: While smaller in size with 303 samples, this dataset still provides a significant amount of data for analysis. Hungarian Institute of Cardiology Heart Disease Dataset: With 294 cases, this dataset offers additional information for researchers to draw conclusions from. Swiss Heart Disease Dataset: This dataset includes data from 303 patient samples and is a valuable resource for researchers studying cardiovascular illnesses. These datasets serve as the foundation for evaluating the performance of various machine learning and deep learning models in predicting and classifying cardiovascular disorders. Table 2 is likely a summary that provides details about the characteristics and attributes of these datasets, facilitating a better understanding of the data used in this research.

Table 2. Listed dataset attributes.

Sl. No.	**Attributes**	**Description**
1.	Sex	Gender (Female = 0, and male = 1)
2.	Age	Patient age
3.	Trestbps	Pressure of blood
4.	Cp	Chest pain (Asymptotic = 4, non-anginal pain = 3, atypical angina = 2, and typical angina = 1)
5.	Fbs	Blood sugar level (fasting = 1 > 120 mg/dL and otherwise = 0)
6.	Chol	Cholesterol sample
7.	Thalach	Utmost heart rate achieved
8.	Restecg	ElectroCardioGraphic results (left ventricular hyperthropy = 2, ST-T wave abnormality = 1 and normal = 0)
9.	Oldpeak	Depression
10.	Exang	Induced angina during exercise (yes = 1 and no = 0)
11	Ca	Main vessels
12.	Thal	Thalassemia (reversible defect = 7, fixed defect = 6 and normal = 3)
13.	slope	Peak of exercise
14.	Num	Heart disease diagnosis (Present = 1 to 4 and absence = 0)

Ethical Considerations

The utilization of patient data from multiple public datasets for cardiovascular disease prediction is supported by strict ethical considerations. These considerations encompass patient privacy, informed consent, and data usage transparency. The data sources, including the Heart Disease UCI, CDD, CCHD, HICHD, and SHD, have followed ethical protocols in data collection.

4.3. Training and Testing Performance

The outcome evaluation of the study involves accessing training and testing performances. Generally, the DL models are validated in terms of accuracy and loss in the training and testing. The performance evaluation in the training and testing process determines the model's ability to learn the disease patterns. Moreover, it evaluates the proposed method's efficiency for unknown data. The proposed work assesses the training and testing performances over increasing the epochs (0 to 100). The datasets were arbitrarily divided into training data (70%) and validation data (30%) for each indicator utilized in prediction tasks. This partitioning strategy is widespread and commonly used in machine learning to ensure that models are trained on a substantial portion of the data. In contrast, a distinct set is used to evaluate their generalization performance. The convergence of the developed model was evaluated based on training and validation accuracy and losses, which indicate how well the model suits the data and its ability to make accurate predictions (Figure 3).

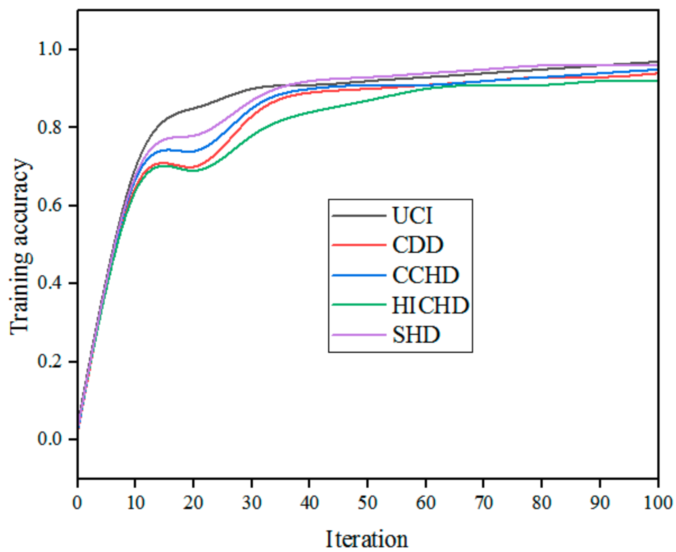


Figure 3. Training accuracy evaluation.

To evaluate how well the proposed PSO-DNN system operates on the training dataset, we look at its training accuracy. This metric measures how well the model fits the training data and how correctly it detects and categorizes cardiac disorders given the input data by comparing the model's projected outputs to the actual labels in the training set. UCI, CDD, CCHD, HICHD, and SHD are the databases used to test the convergence model. Accuracy in training was about 0.96, 0.93, 0.94, 0.9, and 0.95 across these datasets. This accuracy rate represents the percentage of cases in the training dataset that were properly labeled.

The number of errors made by the proposed model on the training dataset is what we call the training loss. More precise illness categorization is predicted by a smaller training loss. The training loss of the model is shown in Figure 4 for several heart disease datasets. The suggested model produced very low error rates of 0.04, 0.07, 0.06, 0.09, and 0.05 for UCI, CDD, CCHD, HICHD, and SHD, respectively. This high degree of accuracy during training is a direct result of the developed model's ability to reduce training loss, as seen by the low error rates observed.

The training accuracy of the designed model, as depicted in Figure 3, demonstrates an increase over the course of iterations. This indicates that, as the model undergoes training, it becomes more adept at correctly classifying the data in the training set, resulting in higher accuracy.

Conversely, the training loss reflects the discrepancy between the actual labels and the labels predicted by the model in the training set. Typically, training loss is computed using functions such as mean square error (MSE) or entropy loss. These loss functions quantify the degree of error between the predicted values and the ground truth labels, providing a measure of how well the model aligns with the training data during the training process. The observed increase in training accuracy and the monitoring of training loss are common practices in machine learning and deep learning to assess the model's learning progress and convergence towards accurate.

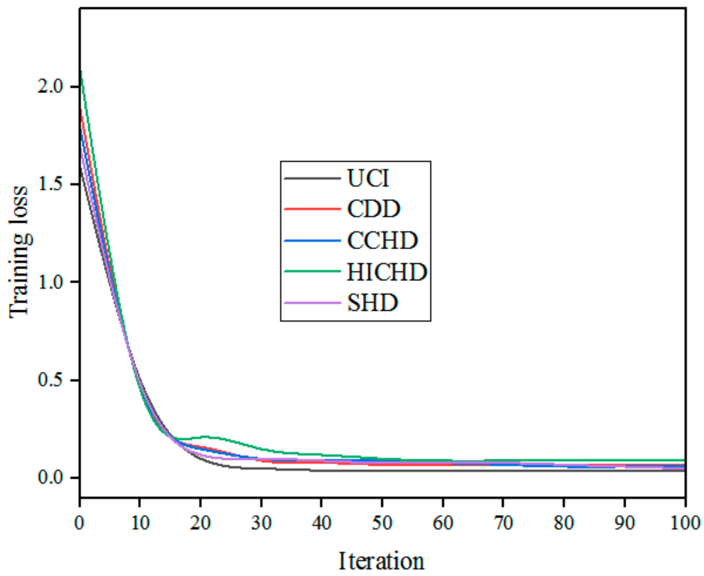


Figure 4. Training loss validation.

The validation accuracy of the developed PCO-DNN model is presented in Figure 5 and is evaluated in relation to the number of iterations. Validation accuracy reflects the model's performance on unseen data, indicating how well it generalizes to previously unseen samples. This is determined by comparing the actual labels to the labels predicted by the model on the validation dataset. For various databases, including UCI, CDD, CCHD, HICHD, and SHD, the designed model achieved high validation accuracy levels. Specifically, it attained validation accuracy rates of approximately 0.94, 0.90, 0.92, 0.89, and 0.93 for these datasets, respectively. These high accuracy values suggest that the PCO-DNN model generalizes well to new, previously unseen data, demonstrating its robustness and effectiveness in making accurate predictions beyond the training dataset.

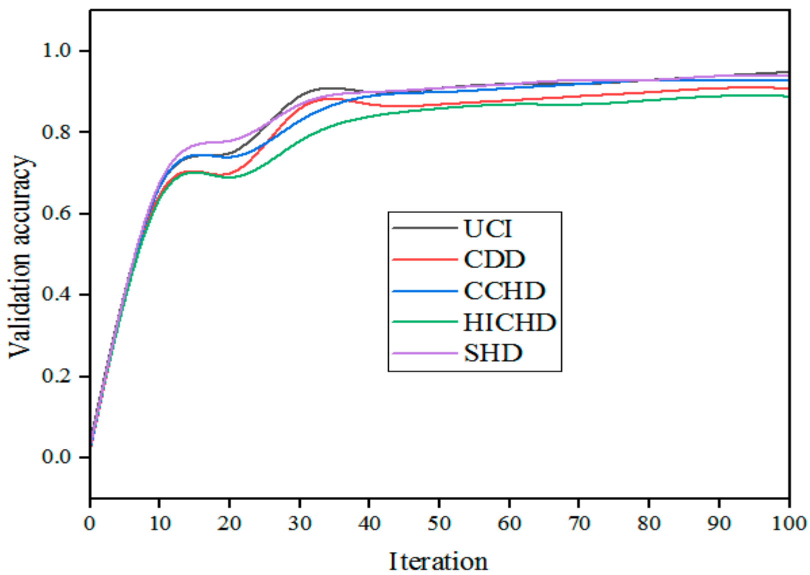


Figure 5. Validation accuracy.

The validation loss, like the training loss, measures the disparity between the model's predicted labels and the actual labels on the validation dataset. Figure 6 illustrates the validation loss of the designed model across different databases. It provides an estimate of how effectively the developed framework performs on unseen data, reflecting the model's ability to make accurate predictions on previously unobserved samples. For various databases, including UCI, CDD, CCHD, HICHD, and SHD, the designed model achieved low validation loss values. Specifically, the validation loss for these databases was approximately 0.05, 0.09, 0.08, 0.1, and 0.7, respectively. These low validation loss values, in conjunction with the high training and validation accuracy, indicate that the designed model demonstrates strong performance and effectively minimizes errors on both the training and validation datasets. This intensive training and testing performance analysis verified that the proposed framework acquired improved performances like greater accuracy and reduced loss. This improved performance demonstrates that the proposed PCO-DNN method learns the disease patterns and offers high generalization ability (it accurately predicts the unseen ECG data). These improved results illustrate that PCO integration with DNN accurately predicts CVD on unseen ECG data. This suggests the model's ability to generalize well and make accurate predictions on new data, highlighting its overall effectiveness.

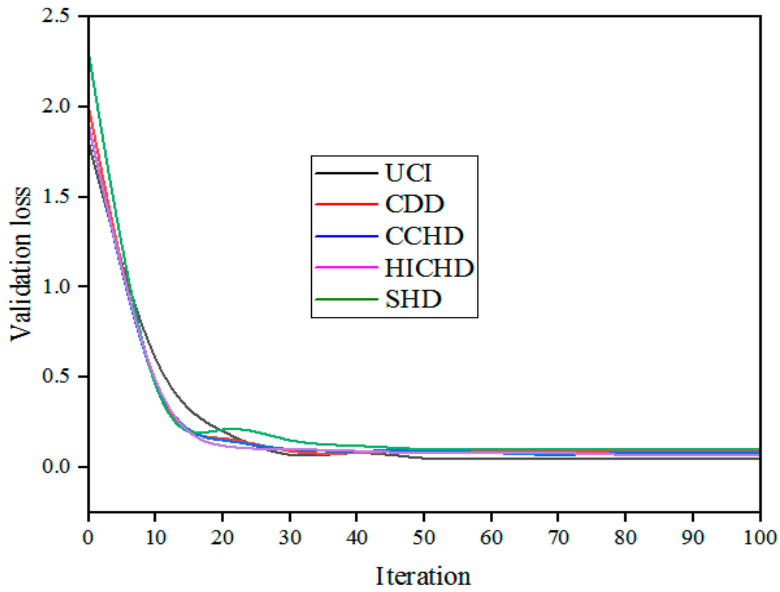


Figure 6. Evaluation of validation loss.

4.4. Evaluation Matrix

The confusion matrix is a valuable tool used for evaluating the performance of machine learning and deep learning models by comparing their classifications to the actual true labels in the dataset. This matrix comprises four significant elements:

True Positive (TP): The number of instances correctly classified as positive (e.g., presence of a condition) by the model. False Positive (FP): The number of instances incorrectly classified as positive by the model when they are actually negative (e.g., the model predicts a condition when it is not present). True Negative (TN): The number of instances correctly classified as negative (e.g., absence of a condition) by the model. False Negative (FN): The number of instances incorrectly classified as negative by the model when they are actually positive (e.g., the model predicts no condition when it is present). These elements form the basis for evaluating the classification performance of the proposed model in terms of the following metrics. Accuracy: It measures how many instances are correctly classified (both positives and negatives) out of the total. Recall: Also known as sensitivity or true positive rate, it assesses the model's ability to correctly identify positive instances. Precision: It evaluates the model's accuracy in classifying positive instances, minimizing false positives. F-Measure: A combination of precision and recall, this metric provides a balance between these two aspects of classification performance. The formulas for calculating these parameters are typically expressed mathematically, as denoted by Equations (15)–(18). These metrics are fundamental in assessing how well a model performs in its classification tasks and are essential for gauging its overall effectiveness.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{15}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{16}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{17}$$

$$\text{F} - \text{measure} = 2 \times \left(\frac{\text{Precsion} \times \text{Recall}}{\text{Precision} + \text{Recall}} \right) \tag{18}$$

The confusion matrix for the developed work is represented in Figure 7. TP indicates the case where the designed model exactly detects the positive class when the true label is also positive. The TN indicates the presented model correctly detects the negative class when the true label is negative. Consequently, the FP represents the case where the designed model incorrectly detects the positive class when the true label is negative. On the other hand, the TN denotes the case where the designed model incorrectly identifies the negative class when the true label is negative.

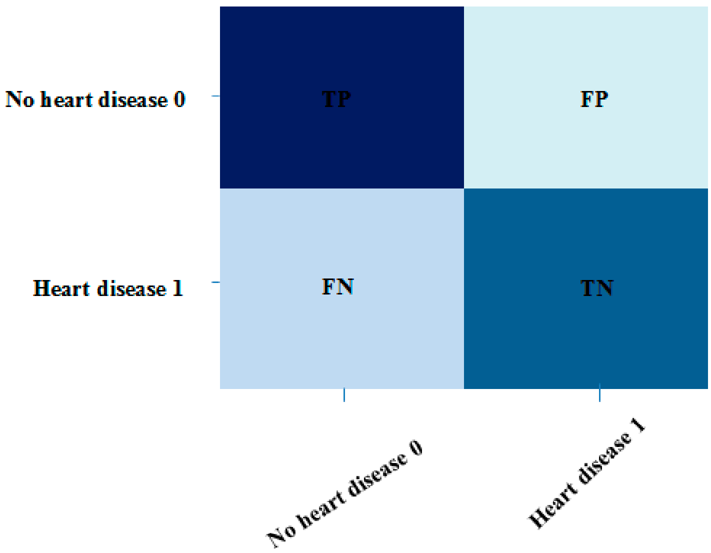


Figure 7. Confusion matrix.

The developed model's performance was assessed individually for five different databases, and then the average performance was calculated. Here are the results for each database: Heart Disease UCI Database: Accuracy 96.12%, Precision 96.43%, Recall 95.59%, and F-measure 95.96%; CBB Database: Accuracy 92.47%, Precision 92.32%, Recall 93.42%, and F-measure 95.71%; Cleveland Clinic Heart Disease (CCHD) Dataset: Accuracy 95.08%, Precision 95.64%, Recall 94.78%, and F-measure 94.45%; Hungarian Institute of Cardiology Heart Disease (HICHD) Dataset: Accuracy 93.13%, Precision 93.90%, Recall 94.78%, and F-measure 94.45%; Swiss Heart Disease (SHD) Dataset: Accuracy 94.29%, Precision 94.25%, Recall 94.01%, and F-measure 93.7%

These performance metrics provide insights into how well the model performs for each individual database in terms of accuracy, precision, recall, and F-measure. The average performance, calculated by considering all these databases, provides a comprehensive measure of the model's overall effectiveness in predicting and classifying cardiovascular heart diseases.

The proposed model performance over different datasets is tabulated in Table 3. Furthermore, the system robustness was determined to evaluate the stability of the model. The system robustness defines the capacity of the proposed hybrid PCO-DNN framework to consistently produce accurate and reliable predictions across different scenarios and conditions. The more robust a system is, the more it can withstand disturbances in the environment, variations in the input data, and other stresses. Further, the consistent performance of the system over different datasets demonstrates the robustness of the designed model.

Table 3. Proposed model performance over different datasets.

Databases	Accuracy (%)	Precision (%)	Recall (%)	F-Measure (%)
Heart disease UCI	96.12	96.43	95.59	95.96
CDD	92.47	92.32	93.42	93.17
CCHD	95.08	95.64	94.98	95.71
HICHD	93.13	93.90	94.78	94.45
SHD	94.29	94.25	94.01	93.70
Average performance	93.6738	92.2160	91.5012	93.5935

4.5. Performance Analysis

The findings of the comparative study, which was carried out to show the value of the suggested cardiovascular disease prediction module, are covered in this part. This section discusses the Predator Crow-performance DNN's training % and K-fold value evaluation. The techniques utilized for the comparative study include random forest (RF) [30,31], K-nearest neighbor (KNN) [32,33], Deep Neural Network (DNN) [34,35], Marine Predator–Deep Neural Network (MPA-DNN) [36,37], and Crow Search Algorithm-Based Deep Neural Network (CSA–DNN) [38].

4.5.1. Performance Analysis in Terms of Training Percentages

In this module, the developed model performances such as accuracy, precision, recall, and F-measure are evaluated at different training percentages as 40%, 50%, 60%, 70%, 80%, and 90%. Similarly, the overall results of the proposed method for different training percentages at epoch 100 are tabulated in Figure 8. From the 100 epochs, 40% attains 92.8423, 50% attains 93.8721, 60% attains 94.2598, 70% attains 94.2841, 80% attains 94.6311, and 90% attains 94.8129. It can be seen from the 100 epochs that 40% attains 92.9053, 50% attains 93.9698, 60% attains 94.5135, 70% attains 94.5988, 80% attains 95.8849, and 90% attains 96.6394. It can be seen from the 100 epochs that 40% attains 90.5086, 50% attains 91.4834, 60% attains 91.5337, 70% attains 91.7043, 80% attains 91.7576, and 90% attains 92.4937. It can be seen from the 100 epochs that 40% attains 93.8579, 50% attains 94.0928, 60% attains 94.5511, 70% attains 95.2771, 80% attains 95.3287, and 90% attains 95.8821.

4.5.2. Performance Evaluation Based on the K-Fold Value

In this module, the performances of the proposed model were evaluated for different k-fold values as 1, 2, 3, 4, 5, and 6. The k-fold cross-validation represents partitioning the data into multiple subsets for iterative model training and testing. The results from different k-fold values offer insights into the model's consistency and performance under various conditions. Selecting an appropriate k value is crucial for reliable and consistent model predictions when applied to new, unseen datasets. The outcome parameters such as accuracy, precision, recall, and f-measure are examined for different k-fold values at 100 epochs. Similarly, the performances of the system for different k-fold values at epoch 100 are tabulated in Figure 9.

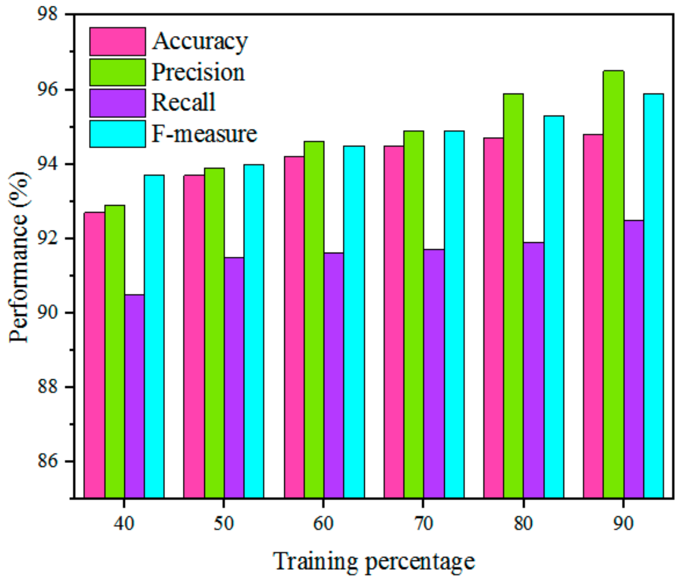


Figure 8. Overall training percentages at epoch 100.

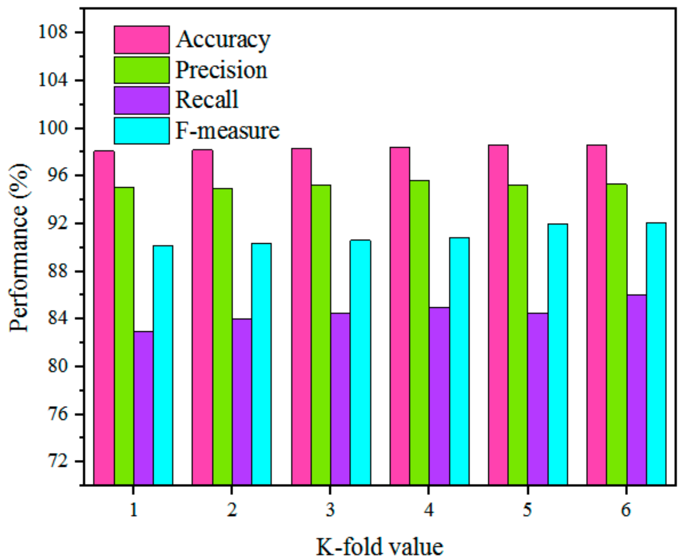


Figure 9. Overall K-fold at epoch 100.

It can be seen from the 100 epochs that 40% attains 91.0155, 50% attains 91.5571, 60% attains 91.6385, 70% attains 92.3281, 80% attains 92.5891, and 90% attains 93.0546. It can be seen from the 100 epochs that 40% attains 90.3522, 50% attains 91.8849, 60% attains 91.9791, 70% attains 91.9062, 80% attains 93.7405, and 90% attains 94.2889. It can be seen from the 100 epochs that 40% attains 90.2731, 50% attains 90.4653, 60% attains 90.8469, 70% attains 91.9062, 80% attains 92.1688, and 90% attains 92.8626. It can be seen from the 100 epochs that 40% attains 90.4641, 50% attains 91.5405, 60% attains 91.9150, 70% attains 92.7053, 80% attains 92.7117, and 90% attains 92.9523.

4.6. Performance Comparison

The comparison of approaches that are based on K-fold [39] and training percentages is discussed in this section. The strategies considered for comparison with the proposed Predator Crow–DNN are the random forest classifier [30,31], K-nearest neighbor classifier [32,33], DNN classifier [34,35], marine predator–deep neural network (MPA–DNN) [36,37], and the Crow search algorithm-based deep neural network (CSA–DNN) [38].

4.6.1. Performance Evaluation Based on Training Percentage

In this section, we assessed the performance of the proposed model using various algorithms, including RF, KNN, DNN, MPA-DNN, and CSA-DNN. We evaluated these performances at different training percentages: 40, 50, 60, 70, 80, and 90. The results of our comparative analysis against traditional algorithms are depicted in Figure 10. Figure 10a specifically presents a comparison of system accuracy with conventional algorithms. The comparison of accuracy performance clearly demonstrates that the PCO-DNN algorithm, which we proposed, achieved higher accuracy compared to existing models. Furthermore, it is worth noting that as the training percentage increases (indicating a higher training ratio), the model's accuracy also increases. This suggests that the model performs better when it has access to more training data.

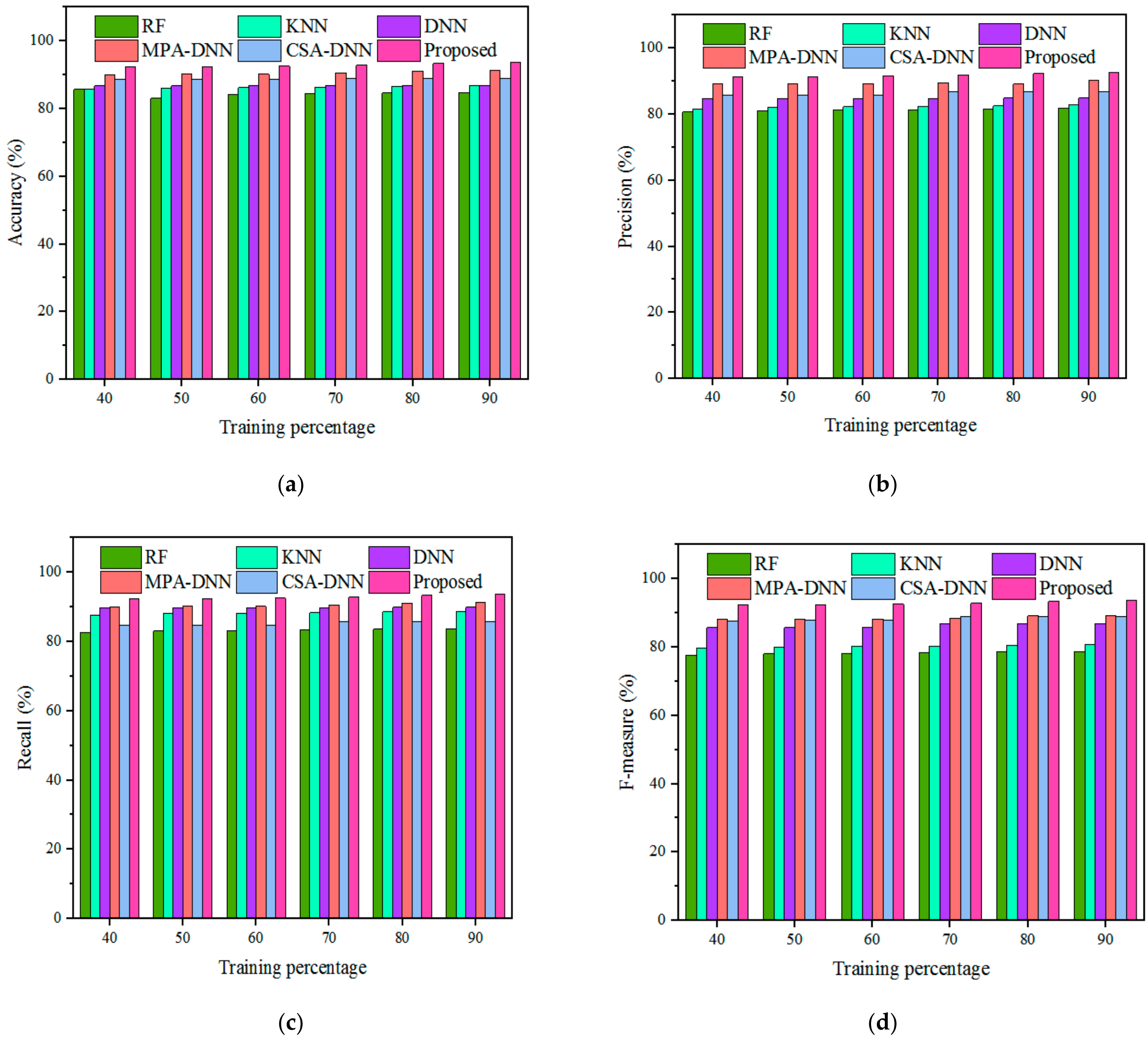


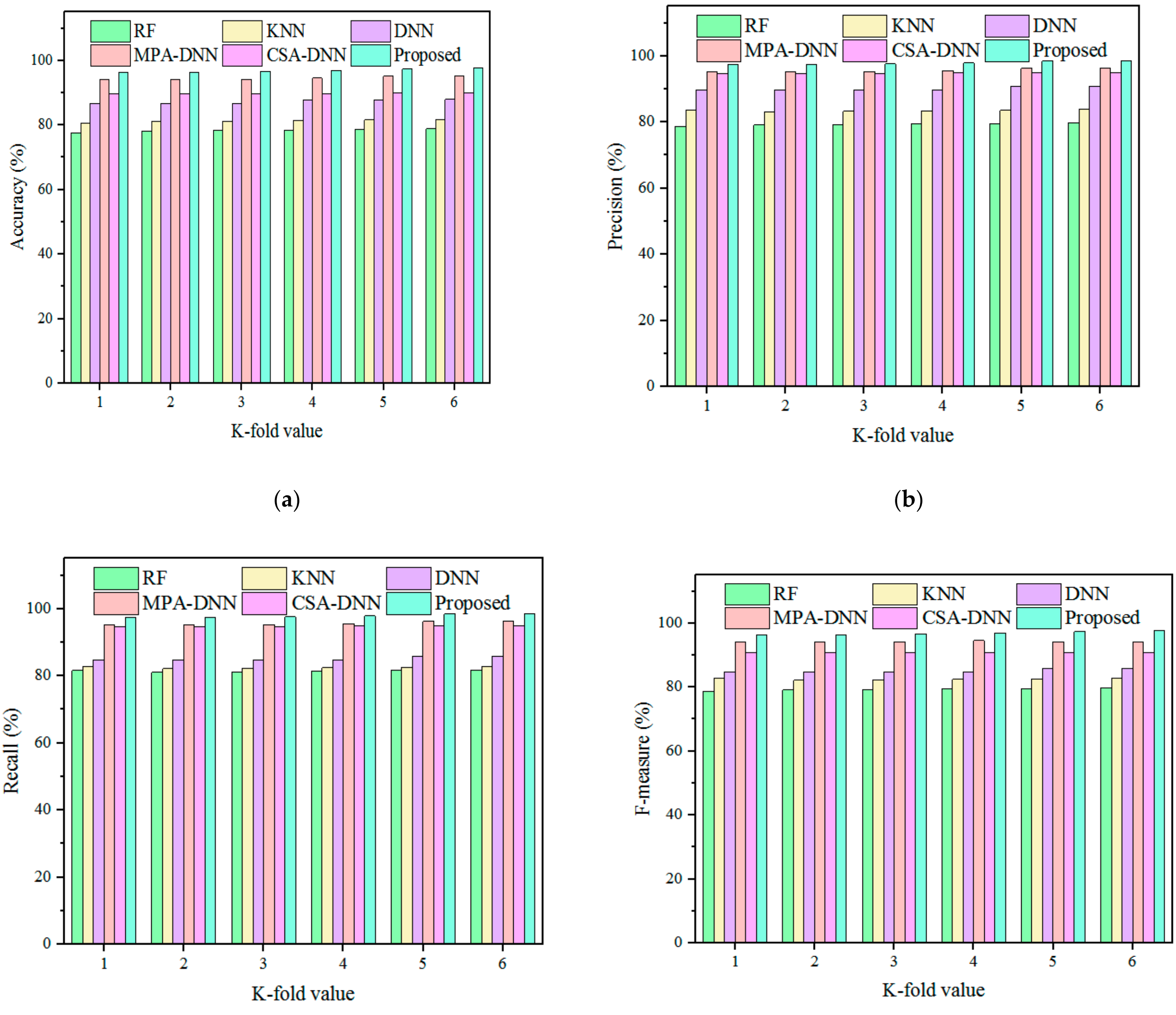
Figure 10. Comparisons of performances in terms of training rate: (**a**) accuracy, (**b**) precision, (**c**) recall, and (**d**) F-measure.

Next, we turn our attention to the precision performances of the various algorithms, as demonstrated and compared in Figure 10b. This evaluation of precision indicates that the approach we designed achieved a superior precision rate when compared to existing models. This highlights the effectiveness of our approach in predicting cardiovascular diseases in comparison to conventional models.

Similarly, the recall and f-measure of these algorithms are assessed in Figure 10c,d. The comparison of recall and f-measure reveals that our model outperformed existing models in both these aspects, further emphasizing the enhanced performance of our designed approach in predicting cardiovascular diseases.

4.6.2. Performance Evaluation Based on K-Fold Value

In this section, we conducted an evaluation of the proposed model's performance alongside established techniques, including RF, KNN, DNN, MPA-DNN, and CSA-DNN. These assessments were carried out with varying K-fold values, specifically 1, 2, 3, 4, 5, and 6. Figure 11 serves as a platform for comparing the system performances with traditional deep learning (DL) algorithms. Figure 11a specifically illustrates the accuracy performance in comparison with existing techniques.



(**a**) (**b**) (**c**) (**d**)

Figure 11. Comparisons of performances relative to k-fold value: (**a**) accuracy, (**b**) precision, (**c**) recall, and (**d**) F-measure.

Our comparative analysis of K-fold values demonstrates that the proposed model consistently achieved higher accuracy than the other models. Consequently, Figure 11b showcases a comparison of precision performance when evaluated against existing techniques. The comparison of the presented model recall with existing techniques is presented in Figure 11c. The recall comparison illustrates that the designed model attained a greater recall rate than the existing algorithms. This states that the proposed algorithm is more efficient in predicting cardiovascular diseases. Finally, the F-measure of the proposed model is evaluated with conventional models, as displayed in Figure 11d.

Table 4 presents the comparison of average performances of different techniques in terms of training percentage and k-fold value. From the intensive comparative study, it is proven that the proposed algorithm attained better results compared to other models. This illustrates that the designed algorithm is more effective and accurate in predicting cardiovascular diseases than the conventional models.

Table 4. Comparative discussion with DL methods.

Sl. No.	**Evaluation Means**	**Metrics**	**Methods**					
			RF	**K–NN**	**DNN**	**MPA–DNN**	**CSA–DNN**	**Proposed Predator Crow–DNN**
1	Training percentage	Accuracy(%)	85.3002	88.1145	89.2505	92.2818	89.8319	93.6738
		Precision(%)	81.2108	82.9088	85.5113	89.0796	86.7082	92.2160
		Recall(%)	83.7403	88.0766	89.2590	90.2271	89.3416	91.5012
		F1-measure(%)	78.2058	80.8334	85.8663	89.8542	88.3338	93.5935
2	K-fold value	Accuracy (%)	79.2787	81.5035	87.5954	95.2882	90.4716	96.6665
		Precision (%)	79.9980	84.6887	89.8256	96.7134	95.5438	97.5256
		Recall(%)	82.1228	82.8578	84.1233	95.0752	95.0256	97.0953
		F1-measure %)	78.7010	81.0823	85.7137	94.9078	90.0725	96.4242

4.7. Comparison of Model Performances with Existing Techniques

In this section, we conducted a comprehensive comparison of the performance of the designed model in terms of precision, F-measure, accuracy, and recall. These evaluations were made in relation to several recent existing techniques, including, Support Vector Machine with Artificial Neural Network (SVM-ANN) [40], Artificial Neural Network-based Cardiovascular Disease Prediction (ANNbCDP) [41], Multi-Layer Perceptron for Enhanced Brownian Motion based on Dragonfly Algorithm (MLP-EBMDA) [42], Genetic Algorithm-based Neural Network (GAbNN) [43], Genetic Algorithm with Particle Swarm Optimization (GA-PSO) [44], Multi-Label Active Learning-based Machine Learning (MALbML) [45], Harris Hawk Optimization-based Clustering Algorithm (HHObCA) [46], Bayesian Optimization-based Extreme Gradient Boosting (BObEGB) [47], and Harris Hawk Optimization with Fuzzy Long Short-Term Memory (HHO-FbLSTM) [48]. This thorough comparison allows us to gauge the effectiveness and superiority of the designed model over these existing techniques across multiple performance metrics.

In the performance evaluation, the designed model exhibited impressive results, achieving an accuracy of 93.6738%, precision of 92.2160%, recall of 91.5012%, and an F-measure of 93.5935%. In contrast, existing methodologies such as SVM-ANN, ANNbCDP, MLP-EBMDA, GAbNN, GA-PSO, MALbML, HHObCA, BObEGB, and HHO-FbLSTM achieved the following performance metrics. SVM-ANN: Accuracy 87.16%, Precision 88.05%, Recall 86.23%, and F-measure 87.5%; ANNbCDP: Accuracy 85.23%, Precision 84.35%, Recall 85%, and F-measure 84.72%; MLP-EBMDA: Accuracy 89.32%, Precision 90.07%, Recall 90.54%, and F-measure 90.32%; GAbNN: Accuracy 86.98%, Precision 87.46%, Recall 87.01%, and F-measure 86.92%; GA-PSO: Accuracy 89.21%, Precision 90.23%, Recall

89.43%, and F-measure 89.56%; MALbML: Accuracy 79.98%, Precision 80.34%, Recall 80.54%, and F-measure 79.31%; HHObCA: Accuracy 85.98%, Precision 87.12%, Recall 86.09%, and F-measure 87.05%; BObEGB: Accuracy 85.49%, Precision 84.37%, Recall 84.95%, and F-measure 84.42%; HHO-FbLSTM: Accuracy 90.76%, Precision 91.54%, Recall 90.03%, and F-measure 90.65%. Figure 12 provides a visual representation of the comparative performance of these different techniques. It is evident from this analysis that the proposed PCO-DNN framework outperformed the existing intelligent and optimization methods across multiple performance measures, highlighting its effectiveness in the context of predicting cardiovascular diseases.

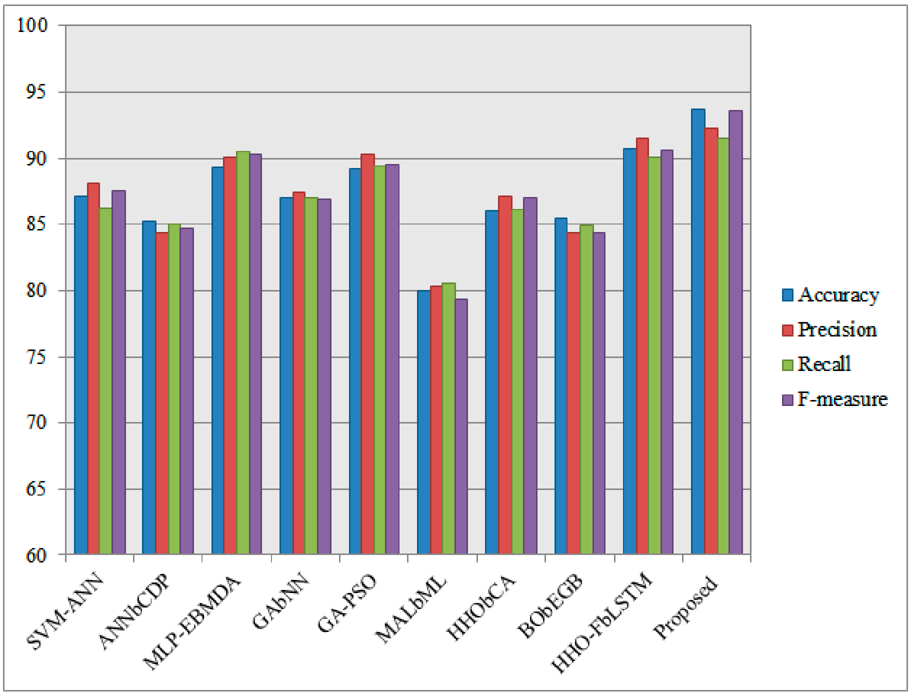


Figure 12. Comparisons of system performances with existing techniques.

4.8. Comparison of Computational Time

Computational time refers to the total time required for the designed model to execute various tasks, encompassing data pre-processing, feature engineering, optimization, and classification. Notably, the designed model demonstrated exceptional efficiency with a remarkably low computational time of 1 s. This 1 s duration can be broken down as follows: data pre-processing 0.2 s, feature engineering 0.3 s, optimization 0.4 s, and classification: 0.1 s. This efficient utilization of time underscores the model's effectiveness and speed in carrying out these critical tasks (Table 5).

Table 5. Computational complexity analysis.

Tasks	Time (s)
Data pre-processing	0.2
Feature Engineering	0.3
Optimization	0.4
Classification	0.1
Total computational time	1.0

Table 4 demonstrates the efficiency of the proposed model in terms of computational time, a comparison was made with the computational time required by recent existing techniques. The following techniques were used for this comparison: SVM-ANN, ANNbCDP, MLP-EBMDA, GAbNN, GA-PSO, MALbML, HHObCA, BObEGB, and HHO-FbLSTM. These obtained the following computational times: SVM-ANN 6.98 s, ANNbCDP 7.54 s, MLP-EBMDA 5.7 s, GAbNN 6.98 s, GA-PSO 7.34 s, MALbML 8.09 s, HHObCA 6.3 s, BObEGB 6.7 s, and HHO-FbLSTM 5.67 s. Figure 13 illustrates the computational time comparison, making it evident that the proposed model consumed significantly less time when compared to these existing techniques. This demonstrates the efficiency and speed of the proposed model in carrying out its tasks.

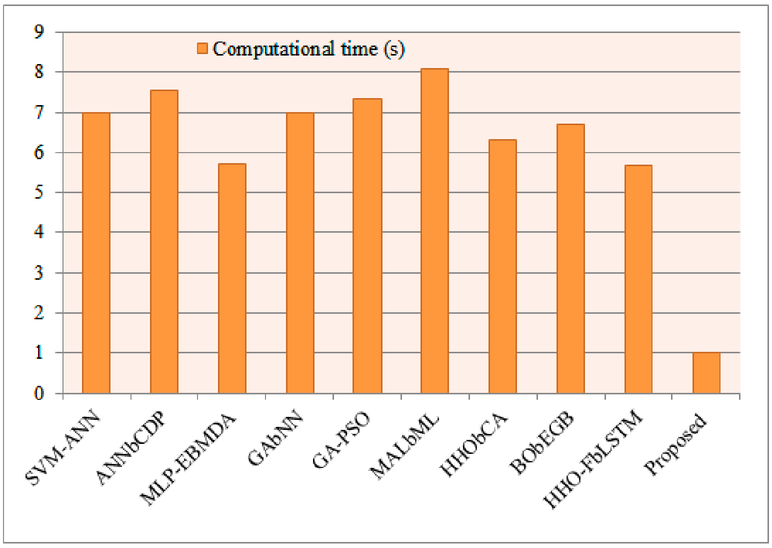


Figure 13. Computational analyses.

4.9. Experimental Findings

The proposed Predator Crow–DNN model performed well, achieving the best accuracy, recall, F1-measure, and precision results. Consequently, the proposed method compared with the conventional state of the methods detailed in the literature is given in Table 6. As a result, the developed scheme eliminate the training flaws at the outset. The features are then extracted based on the aspects of the cardiovascular disease-affected parts. As a result, the advanced Predator Crow–DNN technique improves the performance.

Table 6. Overall performance metrics comparison.

Methods	Performance Assessment with Key Metrics			
	Accuracy	**Precision**	**Recall**	**F1-Measure**
RF	85.3002	81.2108	83.7403	78.2058
K–NN	88.1145	82.9088	88.0766	80.8334
DNN	89.2505	85.5113	89.2590	85.8663
MPA–DNN	92.2818	89.0796	90.2271	89.8542
CSA–DNN	89.8319	86.7082	89.3416	88.3338
LSTM [1]	88.42	92.4	82.4	91.05
Revolutionary methods [2]	88.7	87.5	92.8	90
Scaled three-tier system [3]	NE	46.8	62.3	NE
CSO–CLSTM [4]	97.26	NE	NE	NE
Hybrid fuzzy-based tree-based method [5]	98.30	NE	NE	NE
Random Forest classifier [6]	97.26	NE	NE	NE

Table 6. *Cont.*

Methods	Performance Assessment with Key Metrics			
	Accuracy	Precision	Recall	F1-Measure
Deep learning-based IoT [7]	NE	72.65	72.6	62.4
The smart sports wristband system [8]	98.94	NE	NE	NE
SVM-ANN	87.16	88.05	86.23	87.5
ANNbCDP	85.23	84.35	85	84.72
MLP-EBMDA	89.32	90.07	90.54	90.23
GAbNN	86.98	87.46	87.01	86.92
GA-PSO	89.21	90.23	89.43	89.56
MALbML	79.98	80.34	80.54	79.31
HHObCA	85.98	87.12	86.09	87.05
BObEGB	85.49	84.37	84.95	84.42
HHO-FbLSTM	90.76	91.54	90.03	90.65
Proposed PCO-DNN	93.6738	92.2160	91.5012	93.5935

NE: Not Evaluated.

The exceptional performance measure comparisons are tabulated in Table 6, and the proposed Predator Crow–DNN obtained the best results in all parameter validations. The comparison shows that the state-of-the-art methods are only focused on accuracy metrics; this lacks the prediction performance for a large amount of data in disease diagnosis. However, the proposed method achieved 93.6738% accuracy, 92.2160% precision, 91.5012% recall, and 93.5935 F1-measure. As a result, the proposed Predator Crow–DNN robustness is confirmed and can efficiently predict cardiovascular diseases.

4.10. Discussion

In this research article, a novel hybrid PCO-DNN framework was developed to accurately predict and classify cardiac diseases. The PCO (Population Crow Optimization) is a unique meta-heuristic optimization approach inspired by the hunting behaviors of crows. This approach allows for effective exploration and exploitation of the search space, leading to improved solutions.

In the PCO-DNN framework, the PCO approach is used to optimize the weights and parameters of the Deep Neural Network (DNN) model. This combines the optimization power of PCO with the strong predictive capabilities of DNN. The main objective of this PCO-DNN model is to enhance the accuracy of cardiac disease classification. By optimizing the parameters and weights of the DNN through PCO, the system can better capture the complex relationships and interconnections in the input data, resulting in superior predictive performance compared to conventional methods.

Furthermore, the PCO technique explores the high-dimensional parameter space of the DNN and effectively searches for optimal hyper-parameter combinations and network structures. This, in turn, enhances the DNN's performance in disease identification. Importantly, this approach addresses the problem of over-fitting often encountered by neural networks and provides better generalization to unseen data. This makes the developed model more reliable in real-world scenarios and demonstrates higher robustness in the disease prediction process.

Additionally, the PCO-DNN model provides interpretability by offering insights into the most relevant features and their impact on disease classification. These advantages make the PCO-DNN system an effective and reliable solution for cardiac disease classification problems.

The research conducted a comprehensive performance evaluation by assessing various metrics, including accuracy, precision, recall, and F-measure, across five different databases. Furthermore, an extensive comparative assessment was carried out to validate the obtained results against existing classification models, demonstrating the effectiveness and superiority of the PCO-DNN approach.

4.11. Limitation and Future Work

While this work presents a promising approach to cardiac disease prediction, it does have some limitations. These limitations include the following:

Data Requirements: The developed model requires a substantial amount of data for training and testing, which might not always be readily available, especially in some healthcare settings or for specific populations.

Feature Selection: This study lacks a comprehensive exploration of feature selection methods, which could help improve the model's efficiency and performance by identifying the most relevant input features.

Execution Measures: The study does not delve into execution measures in depth, which could provide insights into the model's computational efficiency and resource requirements.

Despite these limitations, the developed model has the potential for a wide range of applications in the field of heart disease prediction and healthcare. It can serve as a valuable starting point for further research and development. Here are some potential avenues for improvement and expansion:

Data Enrichment: The model could benefit from an expanded dataset, which could include a more diverse set of patient profiles, medical records, and health-related variables. Additional data could enhance the model's accuracy and applicability.

Feature Selection: The implementation of advanced feature selection techniques could help identify the most informative features, streamlining the model and potentially reducing data requirements.

Application Diversification: The same methods used in this study could be applied to predict other diseases in addition to cardiac diseases. This approach can be extended to predict conditions like coronary artery disease or other health-related issues.

Real-Time Solutions: The development of real-time tools, such as a website or mobile application, could provide immediate access to disease prediction, improving healthcare decision making and patient outcomes.

Continuous Improvement: The real-time application can be regularly updated with new capabilities, ensuring it remains relevant and effective in a dynamic healthcare landscape.

Enhanced Feature Engineering: Further research into feature engineering can help identify and incorporate the most effective input features to enhance the model's forecasting capabilities.

Predicting heart disease demands more than a statistical feature-based approach to localization. Furthermore, cardiac illness cases are categorized into more than ten classifications, such as Coronary Artery illness (CAD), Arrhythmias, and so on; therefore, generalizing a single prediction system needs further consideration.

While this work has limitations, it provides a strong foundation for future research and the development of practical tools for disease prediction and healthcare decision support.

5. Conclusions

Predicting cardiovascular diseases can help in preventing acute, life-threatening cardiovascular events as well as improve the long-term outcome for patients susceptible to serious heart diseases. This article suggests a heart disease risk assessment algorithm using patient data to anticipate heart disorders. Pre-processing is first performed to reduce the noise from the collected data on heart illnesses. The following stage involves extracting the important statistical features from the data and creating a feature representation that serves as the input for the suggested DNN classifier. The proposed Predator Crow Optimization approach, generated by considering the attributes of raiding search agents and crow search agents, is used to tune the DNN classifier's weights to improve performance optimally. Performance measures were used to verify the suggested model's efficacy, and it beat the competition. The proposed method achieves 96.6665%, 97.5256%, 97.0953%, and 96.4242% accuracy, precision, recall, and F1-measure, respectively. In the future, to enhance the precision of heart disease prediction, we will employ a diverse set of feature fusion and selection techniques to identify the most significant characteristics from high-dimensional datasets. Additionally, we will explore a predictive approach that leverages the Internet of Things (IoT). This approach will involve the integration of various data mining strategies with deep learning models, designed for data preprocessing and heart disease prediction within fog networks.

This effort is geared towards broadening the applicability of the suggested framework and increasing its accuracy in making predictions. By incorporating IoT and advanced data processing methods, we aim to further improve the model's ability to predict heart diseases with greater precision.

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