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# An Innovative DOS-Care System using Boosted Binary Harris Hawks Optimization and Gated Recurrent Deep Convolutional Network Classification Mechanisms

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***Abstract:*** In the smart healthcare industry, the Internet of Things (IoT) is frequently used to identify various ailments. It has been observed that the manual detection method takes a long time and may produce detection errors that affect the diagnosis. As a result, an autonomous system is required, which is why deep learning techniques are of great importance. As a result, the concept of fusing illness prediction with Deep Learning (DL) to effectively predict the disease is started. In this study, a revolutionary framework for the detection of diabetes and heart disease using medical data is created. It is known as the Deep Optimized Smart Healthcare (DOS-Care) system. Here, a sophisticated Boosted Binary Harris Hawks (BB-HH) optimization technique is used to lower the dataset's dimensionality in order to accelerate and enhance the performance of the classifier as a whole. Following that, the BB-HH optimization model's features are used to develop the Gated Recurrent Deep Convolutional Network (GRDCNet) technique to classify the type of disease. Additionally, loss function of the GRDCNet is estimated using the Krill Herd Optimization (KHO) technique, enhancing the accuracy of the classifier. The Cleveland, Alizadeh, and PIMA-based heart disease and diabetes datasets, which are the most widely used in this work for performance assessment and validation.

***Keywords:*** *Internet of Things (IoT), Smart Healthcare, Disease Diagnosis, Diabetes, Heart Disease, Feature Optimization, and Deep Learning.*

## 1. Introduction

In recent years, the healthcare industry began utilizing information technology to create innovative applications and improve diagnostic and therapeutic procedures [1, 2]. The primary factors that produce vast amounts of digital data are cutting-edge procedures and scientific theory. The offspring of information technology that are being created in the past few years are advanced clinical applications. The Internet of Things (IoT) [3, 4] is a developing new technology that will connect specific smart things with the system in the forthcoming era. IoT is a collection of various gadgets that are utilized covertly all over the world. One of the main study areas for skin-attachable electronic devices is Health Monitoring. Smart Health Monitoring entails using IoT and electronic sensor devices to manage and operate remotely. The medical industry's use of cutting-edge technological sensors contributes to the development of a new technology known as the Internet of medical things (IoMT) [5, 6]. In order to lower the risk to the patient's life, smart healthcare aims to monitor patients effectively via efficient patient data sharing, immediate care, surveillance, and other applications. The field of smart healthcare requires information technology to provide cutting-edge applications for improving treatment and screening techniques [7]. The largest portion of the structures that generate enormous volumes of digital information are modern methodologies and research hypotheses. Diabetes is an incurable disease that affects people across the world and develops when the human body reduces the ability to generate the hormone insulin. High blood glucose levels in diabetes patients harm the body's organs by causing impairment to those organs. The healthcare models' features include incomplete medical data, blocked information, data warnings, and many more. Skin-attachable sensors that are connected to the IoT and big data have thus arisen in the modern world as a solution to this problem [8, 9]. One of the most significant and challenging health issues nowadays is the automatic diagnosis of heart disease. Heart illness impairs blood vessel function and results in coronary artery infections, which impair the patient's body, particularly among adolescents and elderly individuals. According to the World Health Organization (WHO), cardiovascular diseases are to blame for nearly 18 million deaths worldwide each year [10]. The main issue faced during the medical field's evolution was the demand for newly developed, appropriate forms of technology to provide the greatest services to patients. By using IoT and evolutionary technologies, this problem can be resolved. The use of IoT in the medical field has become more and more common with the innovations of smart devices and sensors. The typical components involved in the smart healthcare system [11] are shown in Fig 1. Wearable devices and diagnostic procedures can be used to detect cardiovascular disorders. In contrast, it is challenging for doctors to diagnose patients swiftly and precisely while still collecting useful risk indicators for heart disease from computerized medical evaluations. Due to the frequent medical tests, these electronic medical records tend to be chaotic and constantly growing in size [12].

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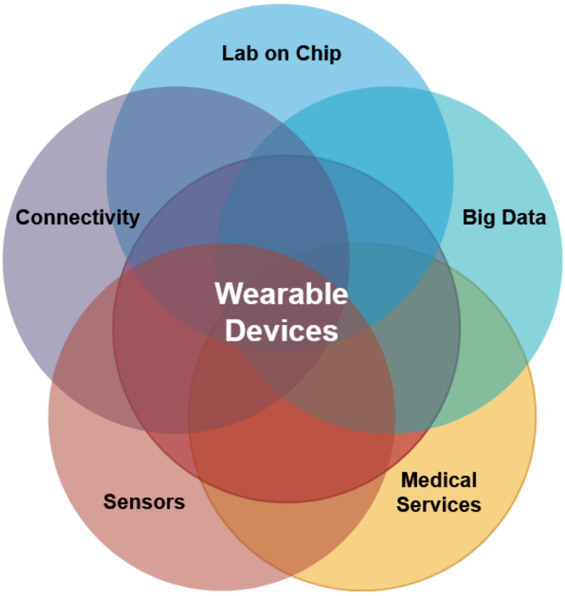



**Fig 1**. Typical components of a smart healthcare system

In order to diagnose cardiac disorders, wearable sensors are currently also used to continually monitor the patient's body inside and outside. However, signal aberrations like missing values and noise contaminate wearable sensor data for heart disease prediction, which lowers system performance and yields erroneous conclusions. The early diagnosis of diseases is crucial for avoiding severe health issues. IoT combined with deep learning techniques [13, 14] is now widely used in numerous sectors. In order to efficiently track patient behaviours and disease-related data to make an accurate diagnosis, [28] the healthcare industry is attempting to adopt IoT-based devices with patients. Unlike in the past, IoT and AI approach today aid in the accurate prediction of a variety of health conditions. In the case of smart healthcare[29], the patient's information is saved on the server and may be downloaded as needed to carry out an appropriate diagnosis. Based on the structural knowledge of the anatomical system, several deep-learning approaches are used for disease diagnosis. The problems [15] with current disease prediction methods are that they don't take into account preprocessing and post-processing methods that improve prediction quality. Additionally, choosing irrelevant features lowers classification accuracy, and failing to take them into account may make computations more complex. Additionally, the classification accuracy is decreased by using deep learning algorithms without taking optimization into account. The suggested model was used to address the aforementioned issues since it makes use of preprocessing, most important feature selection, and optimization based deep learning mechanisms to improve classification accuracy. The original contributions of this research work are given in below:

- In this study, a novel framework, called, a Deep Optimized Smart Healthcare (DOS-Care) system is developed for the diagnosis of diabetes and heart disease from the medical data.
- Here, an advanced Boosted Binary Harris Hawks (BB-HH) optimization mechanism is applied to reduce the dimensionality of the dataset for improving the overall classifier's speed and performance.
- Then, the Gated Recurrent Deep Convolutional Network (GRDCNet) technique is implemented to categorize the type of disease according to the features provided by the BB-HH optimization model.
- Moreover, the loss function of the GRDCNet is optimally computed with the use of the Krill Herd Optimization (KHO) technique, which increases the accuracy of the classifier.
- The most popular heart disease and diabetes datasets from Cleveland, Alizadeh, and PIMA were used in this work for performance assessment and validation.

The following units make up the remaining sections of this article: The thorough literature analysis and data mining techniques utilized to create the framework for smart healthcare are presented in Section 2. The proposed DOS-Care structure is then clearly described in Section 3 along with its flow and examples. Section 4 presents the results of the performance and comparative study utilizing several metrics and well-known datasets. In Section 5, the findings, outcomes, and future scope of the work are summarized.

## 2. Related Works

In a healthcare monitoring system for people with diabetes and heart disease, smart sensors and digital health records are used as essential components. However, it is difficult to extract features from sensory data and healthcare records and then combine them to create organized data. For systems based on machine learning (ML), selecting features from organized data and then giving them useful weights is another difficulty. As a result, this section begins by discussing portable sensor-based systems for diagnosing heart disease and diabetes. Afterwards, it focuses on obtaining information from text data and a combination of features. Additionally, this part provides a succinct overview of the recognition of significant features in healthcare data in the context of diabetes and heart disease prediction.

Mansour, et al [16] implemented an AI-based smart healthcare system for providing appropriate medical services to patients affected by heart disease or diabetes. In this study, the Crow Search Optimization (CSO) based Long Short Term Memory (LSTM) classification methodology is deployed for predicting both heart disease and diabetes from the healthcare data. Saba, et al [17] conducted a comprehensive survey to examine several machine learning and deep learning techniques used for developing an IoT-based smart healthcare framework[30]. A subset of AI called Machine Learning (ML) tries to automate machines with the least amount of human intervention [18]. It can be broadly divided into three categories: semi-supervised learning, reinforcement learning, unsupervised learning, and supervised learning. Both supervised and unsupervised algorithms use mathematical structures and are created to give systems the ability to assess various tasks and learn how to handle them. In supervised learning, the dataset and associated labels (i.e., values or classes) are utilized to train the model. The program receives the input dataset and its pertinent outputs, compares the actual output to the right result to discover flaws, and then modifies the model as required. As a result of its sophisticated object detection and classification methods, ML is quickly advancing in all fields. As it improves services offered by healthcare systems such as disease assessment, precise discoveries, reliable diagnosis, and early disease identification, ML techniques [19] play a vital role in smart healthcare systems. Since medical information is stored digitally, there are several obstacles to overcome until it can be used in modern medical systems. Healthcare data has grown significantly over the past few years, and for correct diagnosis, it needs to be maintained and identified appropriately. ML algorithms can be used to offer solutions to a variety of healthcare issues. DL is a subfield of ML that is heavily focused on algorithms that use neural networks to act like the human brain. The primary benefit of deep learning over regular machine learning is that it does away with the preprocessing, feature extraction, and feature selection processes. Unstructured information including images, text, sensor information, spatial information, etc [20]. respond well to DL algorithms with the processes of feature extraction and optimization. By using a number of elements including inputs, the weights, bias, and data fusion, the deep learning techniques mimic how the human brain functions by performing a variety of tasks in a specific categorization and recognition.

Alsheri, et al [21] presented a comprehensive study to examine the importance of IoT/IoMT-based smart healthcare systems. Moreover, it provides a multi-sensor-based fusion framework for disease identification and classification. Every smart system has more connected gadgets, sensors, and connected devices than ever before. A vast healthcare network can only function if it is equipped with sensing capabilities and the ability to generate crucial information. A great number of connected sensors and IoTs in the healthcare system produce enormous volumes of data for analysis. The data model and knowledge representation model of the entities in the IoT should be compatible. The majority of IoMT devices [22] can be utilized for recognizing and diagnosing illnesses in various healthcare settings, but the data gathered from heterogeneous sensors contain a range of shortcomings including technical errors, exhausted chargers, and communication concerns. The combination of sensors and IoTs can handle changes as background factors, including noise from sensors and the capturing environment, change as they can directly affect system qualities like reliability [23]. To allow the system to adapt to particular circumstances, sharing methods for transfer learning should be implemented. These approaches collect and transmit knowledge from one circumstance to another. Khanna, et al [24] applied a deep learning technique to identify cardiovascular disease from the IoT-integrated medical sensors. In this study, the novel Artificial Flora Optimization (AFO) technique is deployed to optimize the parameters used for disease prediction. Moreover, the Fuzzy Deep Neural Network (FDNN) technique is applied to categorize the type of disease according to the features that are extracted by the Bi-directional LSTM technique. Ali, et al [25] introduced a new health monitoring system based on feature fusion and ensemble deep learning techniques. In this article, researchers introduced a smart healthcare monitoring framework that combines feature fusion techniques with an ensemble deep learning model to increase the precision of heart disease prediction and aid clinicians in making prompt and accurate diagnoses of heart patients. In paper [26], a lightweight and secured smart health monitoring framework is developed for the detection and classification of chronic kidney disease. The authors aim to implement an IoT integrated cloud technology for the disease identification and diagnosis. However, the suggested methodology is complex to implement and it requires more time to disease recognition. Naresh, et al [27] provided a detailed overview of the smart healthcare architecture with the challenges and existing solutions. This study indicated that the IoT based smart healthcare is more useful for elderly people to provide regular or emergency services. The major problems that still exist in conventional IoT-based smart healthcare systems are listed as follows:

- Low reliability.
- Lack of fault tolerance capability.
- Increased latency or delay time.
- Lower energy efficiency.
- Absence of network or node availability.

The proposed effort intends to establish a new smart healthcare framework with the usage of cutting-edge AI mechanisms for the recognition and diagnosis of diabetes and heart disease to address these issues.

## 3. Methods

The proposed Smart Healthcare system utilized for disease detection is fully explained in this section. The unique contribution of this study is the application of cutting-edge mining methods combined with IoT technology to create a Deep Optimized Smart Healthcare (DOS-Care) system that can forecast diabetes and heart disease. In the proposed work, the patient's medical record received from IoT sensors is taken into consideration as input, and the disease diagnosis is carried out using AI techniques to provide the patients with diabetes and heart disease with the proper medicines. The flow of the proposed DOS-Care framework, which comprises the following components:

- Collection of medical data of patients
- Feature extraction
- Boosted Binary Harris Hawks (BB-HH) optimization-based feature selection
- Gated Recurrent Deep Convolutional Network (GRDCNet) based disease prediction
- Parameter tuning using Krill Herd Optimization (KHO)

### 3.1 Methodology of Proposed Work

The early diagnosis of diseases is crucial for avoiding severe health issues. IoT combined with deep learning techniques has become prevalent in numerous sectors. To efficiently track patient behaviours and disease-related data to make an accurate diagnosis, the healthcare industry is attempting to adopt IoT-based gadgets with patients. By using the PIMA, Cleveland, and Alizadeh datasets, a DOS-Care framework is proposed in this study for the prediction of diseases. The obtained data is preprocessed to get rid of any superfluous information, including negative scores or unbounded values. One of the key steps to enhancing the method's performance is preprocessing the data. Additionally, it converts the raw data into usable data. Here, the missing value imputation approach is used to process the healthcare dataset, which eliminates innumerable values for lightning-fast processing. The feature extractor then receives the processed data and extracts only the necessary features for analyzing the data. After being optimized with BB-HH, the retrieved features are then transferred to the classifier where the KHO algorithm is integrated to adjust the parameters of GDRCNet classifier.

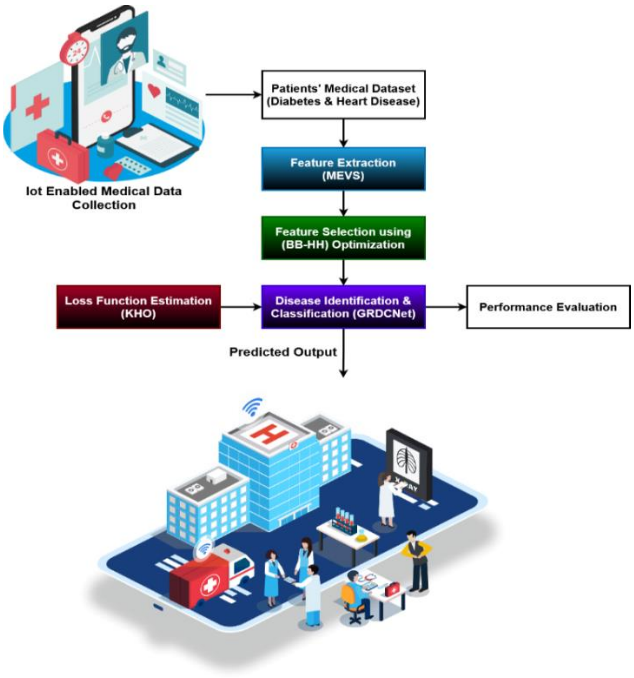



**Fig 2.** The flow of the proposed Deep Optimized Smart Healthcare (DOS-Care) Framework

### 3.2 Feature Extraction

The method of feature extraction ensures an efficient display of the raw input data by removing the important and necessary facts for prediction. In this study, statistical features like variance, mean, standard deviation, and entropy have been collected by feature extraction. The ratio of the total quantity of data present in the repository to the sum of the data is known as the mean, which is a statistical property. The variance is the difference in each data point's mean squared from the mean value. The standard deviation displays the degree of variation or dispersion at each instance of the mean-related data, which is calculated using the variance's shape. Entropy is the likelihood of every potential arrangement of the data.

### 3.3 Boosted Binary Harris Hawks (BB-HH) Optimization-based Feature Selection

The BB-HH optimization technique is used to optimize the number of features for accurate classification after the relevant features have been extracted from the dataset. Since both diabetes and heart disease can be detected by the suggested DOS-Care system and their corresponding medical datasets are large. Therefore, reducing the dataset's dimensionality is crucial to making classification decisions that are accurate and simple at the time of disease prediction. The suggested study uses the BB-HH optimization technique, which offers the best overall solution for selecting the optimal amount of features for the classifier, for this purpose. It is a swarm-based optimizer that was developed based on how Harris hawks communicate with one another to catch fleeing prey. The initialization and updation are two of the phases covered by this optimizer. To choose the initial parameters for BB-HH optimization, the initial setup step is required. The exploration and exploitation processes are carried out at random during the update step. This process is divided into two parts, according to where the hawks are perched. In the exploitation phase, hawks study the intended rabbit and make an effort to use various hunting techniques to deal with the rabbit's escape attempts. During the exploration process, the searching agents explore different terrains in quest of prey (best agent). In each stage, two mechanisms must be carried out with an equal probability as represented in the following model:

$$H(k+1) = \begin{cases} H_v(k) - \rho|H_v(k) - 2\sigma H(k)| & r \geq 0.5 \\ (H_{tar}(k) - H_{avg}(k)) - \tau \times (\partial(U_b - L_b) + L_b) & r < 0.5 \end{cases} \quad (1)$$

$$H_{avg}(k) = \frac{1}{M}\sum_{i=1}^{M} H_i(k) \quad (2)$$

The energy of the prey is used for the transition between two processes in BB-HH. The kinetic energy of the prey drastically decreases when fleeing, hence it is described as a time-varying stochastic parameter as described in the following model:

$$E_g = 2\varepsilon_0(1 - \frac{k}{K}) \quad (3)$$

According to the level of escaping energy, the intensification and diversification operations are performed in this technique. Search agents can use the solutions around the current optimum during the exploitation process. Also, it creates four mechanisms to describe the exploitation phase based on various hawk-hunting techniques and rabbit evasion behaviours. The current location updation is performed as shown in the following equation:

$$H(k+1) = \Delta H(k) - E_g \times |J_s \times H_{tar}(k) - H(k)| \quad (4)$$

$$\Delta H(k) = H_{tar}(k) - H(k) \quad (5)$$

$$J_s = 2 \times (1 - q) \quad (6)$$

The quick dives in HHO are calculated using the Levy flight principle. The last stage is difficult to attack with consecutive quick dives, $E_g$ 0.5 and random value 0.5, in which the searching agents attempt to reduce the gap between the targeted prey and the normal location. Based on the following models, the present spot can be evaluated:

$$G' = H_{tar}(k) - E_g \times |J_s \times H_{tar}(k) - H_{avg}(k)| \quad (7)$$

In the end, the final updated location is determined according to the current location of the final stage as represented in the following equation:

$$H(k+1) = \begin{cases} G', \text{if}(G') < H(k) \\ I', \text{if } G(I') > H(k) \end{cases} \quad (8)$$

To make this optimization more efficient, the hybrid individual is added in this technique before estimating the escaping energy for the current searching agent as indicated in the following model:

$$H_{hyb} = \omega \times H_i + (1 - \omega) \times P_i \quad (9)$$

By using this advanced optimization algorithm, the features are optimally selected for predicting disease before classification. The list of symbols with their explanations is given in Table 1.

**Table 1.** List of symbols and descriptions

| *Parameters* | *Descriptions* |
|---|---|
| $H(k+1)$ and $H(k)$ | Position vectors |
| $k, k+1$ | Iterations |
| $\rho, \sigma, \tau, \partial$ and $r$ | Random numbers |
| $H_{tar}(k)$ | The position vector of the best agent |
| $H_{avg}(k)$ | The average position vector of the current agent |
| $U_b$ and $L_b$ | Upper and lower bounds |
| $M$ | Size of swarm |
| $E_g$ | Escaping energy |
| $\varepsilon_0$ | Random initial state |
| $K$ | Maximum number of iterations |
| $q$ | Random value |
| $J_s$ | Jumping strength |
| $G'$ and $I'$ | Updated location |
| $H_{hyb}$ | Hybrid individual |
| $\omega$ | Weight value |
| $P_i$ | Position vector |

### 3.4 Gated Recurrent Deep Convolutional Network (GRDCNet)

Following feature reduction, the GRDCNet classifier is used to precisely determine the disease type from the patient's medical records. The primary goal of this study is to apply a cutting-edge DOS-Care framework to identify and recognize both diabetes and heart disease. The proposed GRDCNet differs from other deep learning and machine learning methods in that it is more effective, has a higher detection rate, produces fewer false positives, and is better suited to handle huge datasets. A sequential input with potentially varied lengths can be processed by the Recurrent Neural Network (RNN). It describes a repeating concealed state whose activation changes depending on the prior activation. Typically, the Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU)-based RNN architectures are the most common. The more recent version exhibits performance that is comparable to LSTM but requires less memory and processing power. In this study, the GRCNN will be built using GRU frameworks. This architecture serves as a classifier, and its function is to determine whether the medical data is healthy or falls into one of the training set's classes. This is accomplished by feeding the output of the final time step and final recurrent layer to a fully connected layer with activation to acquire the identity vector. This identity vector is eventually transmitted through another fully connected layer during the training phase with softmax activation of N + 1 neurons to distinguish between the healthy and sick classes. Here, the update gate function is estimated with the time step t as represented below:

$$c_t^m = \varphi(\max out(\omega_c^m * a_t^m + v_c^m * \hbar_{t-1}^m)) \tag{10}$$

Where, $c_t^m$ is the update gate, time t, $\varphi$ is the sigmoid function, $a_t^m$ is the input, $\hbar_{t-1}^m$ is the hidden state and $*$ is the convolution operator. Consequently, the reset gate $r_i^m$ the function is estimated by using the following model:

$$r_i^m = \varphi(\max(\omega_r^m * a_r^m + v_r^m * \hbar_r^m)) \tag{11}$$

It is decided whether or not to erase some of the preceding information using the reset gate. These convolutional layers are capable of being thought of as filter banks that have been tuned and trained to effectively detect illness. Compared to those derived using fully connected units, they tend to be more discriminative. The update activation is the final gate that is computed by using the following equation:

$$\tilde{\hbar}_t^m = \mathbf{tanh}(\mathbf{maxout}(\omega_\hbar^n * a_t^n + v_\hbar^n * (r_i^n \odot \hbar_{t-1}^n))) \tag{12}$$

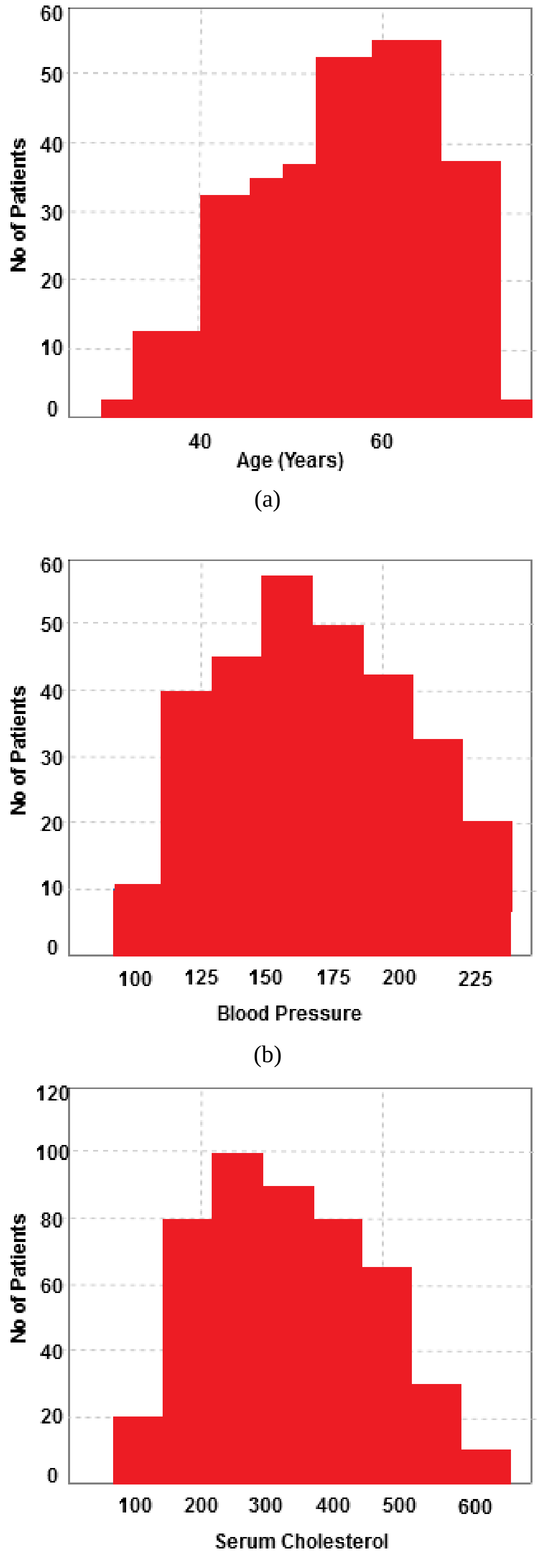
Where, $\omega_c^m$, $\omega_r^m$, $\omega_\hbar^n$ are the model parameters, $v_c^m$, $v_r^m$, $v_\hbar^n$ are the filters, **tanh** (.) indicates the tanh function, and $\odot$ represents the element-wise operation. In this classifier, the binary cross-entropy loss function is estimated with the target input and output classes. To make an accurate disease prediction, the KHO technique is used to optimally compute the loss function, which improves the training and testing efficiency of the classification process. The loss function is computed as represented in the following model:

$$\mathbf{L} = \sum_{x=1}^{X} m_x \cdot \log(\varphi(c_x)) + (1 - m_x) \cdot \log(1 - \varphi(c_x)) + \alpha \tag{13}$$

Where **L** is the loss function, $m_x$ is the mask value, and $\alpha$ is the optimal value estimated by using the KHO technique.

## 4. Results and Discussion

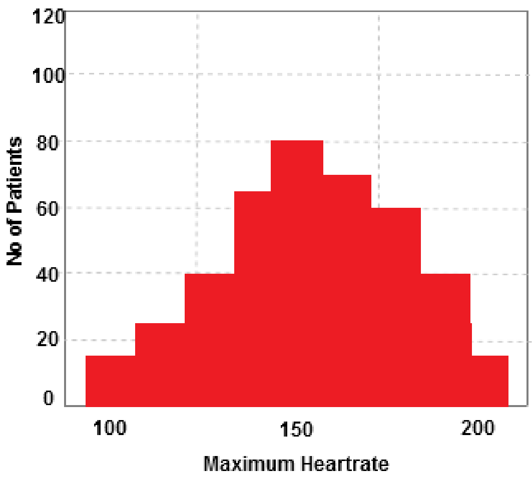
The suggested approach for disease prediction is put into practice using the MATLAB program. The proposed method is implemented effectively and simply using MATLAB software, which has been integrated with the Windows 10 OS and 64-bit operating systems having 16 GB RAM. The main purpose of this study is to develop a smart healthcare framework for predicting both diabetes and heart diseases from the patient's medical data obtained through IoT sensors. For validating the performance of the proposed methodology, the popular diabetes dataset known as PIMA and heart disease datasets including Cleveland, and Z-Alizadeh datasets have been used in this study. The sample records of the Cleveland dataset are shown in Fig 3 (a) to €.



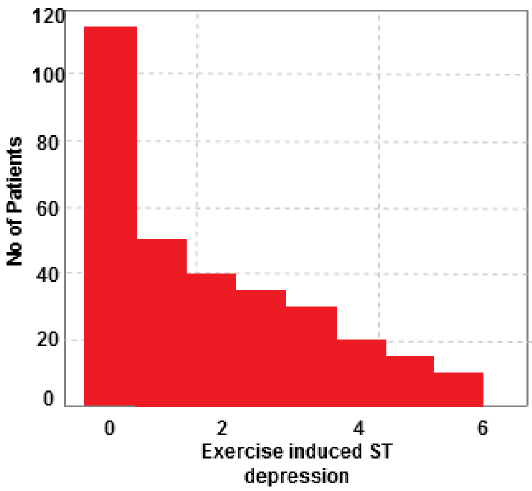

(a)

(b)

(c)




(d)




(e)

**Fig 3.** Sample records of Cleveland dataset

The mathematical definition of accuracy is the proximity of the predicted output generated by the proposed method to the reference value.

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

According to the following mathematical model, sensitivity is the capacity to precisely recognize patients with diabetic disease using the proposed approach for accurate predictions:

$$\textbf{Sensitivity} = \frac{\textbf{TP}}{\textbf{TP+FN}} \tag{16}$$

Specificity is the capability to accurately recognize patients with non-diabetic disorders by using the proposed methodology, which is shown in the following model:

$$\textbf{Specificity} = \frac{\textbf{TN}}{\textbf{TN+FP}} \tag{17}$$

The accuracy and sensitivity of the heart disease classification model are measured by precision and recall, respectively. The discrepancy between actual and anticipated values is measured using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), respectively.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{18}$$

$$\text{RMSE} = \sqrt{\frac{1}{\text{X}}\sum_{\text{i}=1}^{\text{X}}(\text{a}_\text{i} - \widehat{\text{a}}_\text{i})^2} \tag{19}$$

$$\text{MAE} = \frac{1}{\text{X}}\sum_{\text{i}=1}^{\text{X}} |\text{a}_\text{i} - \widehat{\text{a}}_\text{i}| \tag{20}$$

Where TP is the True Positive, TN is the True Negative, FP is the False Positive, FN indicates the FALSE NEGATIVE, X is the total number of observations, $\text{a}_\text{i}$ is the actual value, and $\widehat{\text{a}}_\text{i}$ denotes the predicted value. The accuracy, sensitivity, and specificity of the traditional and proposed deep learning algorithms utilized in the smart healthcare system for predicting heart disease are validated and compared in Table 2 and Fig. 4 respectively. As a result, Table 3 and Fig 5 illustrate how the various optimization integrated classification algorithms are tested and contrasted using the heart disease dataset. The prediction findings clearly show that, in comparison to previous approaches, the suggested DOS-Care framework offers effective results.

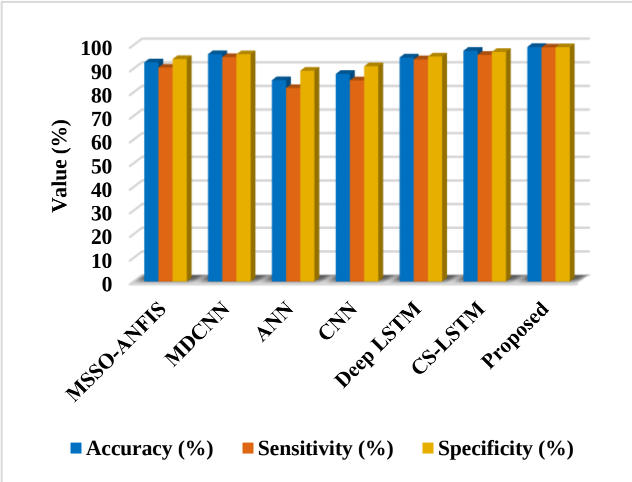



**Fig 4.** Comparison using heart disease dataset

**Table 2.** Comparative analysis with different classification techniques using heart disease dataset

| *Methods* | *Accuracy (%)* | *Sensitivity (%)* | *Specificity (%)* |
|---|---|---|---|
| MSSO-ANFIS | 92.70 | 90.47 | 94.07 |
| MDCNN | 96.17 | 94.92 | 96.13 |
| ANN | 85.15 | 81.82 | 89.14 |
| CNN | 87.80 | 85.08 | 91.04 |
| Deep LSTM | 94.74 | 93.97 | 95.17 |
| CS-LSTM | 97.59 | 95.87 | 97.09 |
| Proposed method | 99.2 | 99 | 99.1 |

**Table 3.** Comparative analysis with different optimization + deep learning techniques using heart disease dataset

| **Methods** | **Accuracy (%)** | **Sensitivity (%)** | **Specificity (%)** |
|---|---|---|---|
| PSO-CCNN | 94.08 | 93.62 | 94.54 |
| GWO-CCNN | 93.66 | 92.64 | 94.68 |
| WOA-CCNN | 93.44 | 92.08 | 94.8 |
| DHOA-CCNN | 94.81 | 99.26 | 90.36 |
| GSO-CCNN | 94.9 | 93.48 | 97.25 |
| Proposed method | 99.3 | 99.3 | 99.1 |

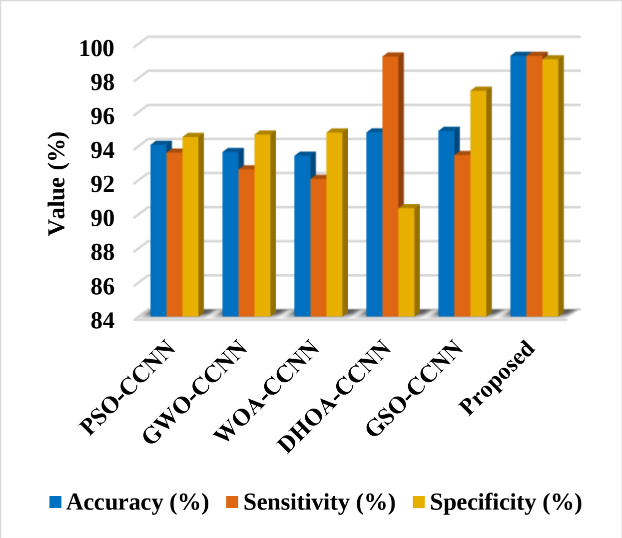



**Fig 5.** Comparison with optimization-based deep learning model using heart disease dataset

As a result, using the heart disease dataset, Table 4 and Fig. 5 evaluate the precision, f1-score, and Matthews Correlation Coefficient (MCC) of the traditional optimization-included classification algorithms. Additionally, the false detection performance analysis of the existing and suggested optimization integrated classification methodologies is compared in Table 5 and Fig 6. The various evaluation indicator types are primarily estimated in this assessment to demonstrate the effectiveness of the suggested DOS-Care system. It is evident from the results that the suggested technique, when combined with BB-HH optimization and GDRCNet techniques, offers better performance results.

**Table 4**. Detection performance using heart disease dataset

| *Methods* | *Precision (%)* | *F-score (%)* | *MCC (%)* |
|---|---|---|---|
| PSO-CCNN | 94.4 | 94 | 88.16 |
| GWO-CCNN | 94.56 | 93.59 | 87.3 |
| WOA-CCNN | 94.65 | 93.35 | 86.91 |
| DHOA-CCNN | 91.14 | 95.03 | 89.97 |
| GSO-CCNN | 98.07 | 95.72 | 89.83 |
| Proposed method | 99.1 | 99 | 99.1 |

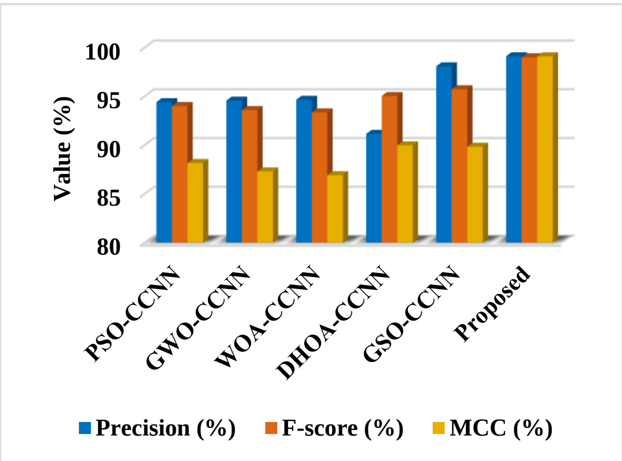



**Fig 5.** Detection performance analysis with optimization-based deep learning model using heart disease dataset

**Table 5.** False prediction analysis

| *Methods* | *FPR* | *FNR* | *NPV* | *FDR* |
|---|---|---|---|---|
| PSO-CCNN | 0.05 | 0.06 | 0.94 | 0.055 |
| GWO-CCNN | 0.0532 | 0.0736 | 0.9468 | 0.054 |
| WOA-CCNN | 0.0521 | 0.0792 | 0.948 | 0.053 |
| DHOA-CCNN | 0.0964 | 0.0074 | 0.9036 | 0.088 |
| GSO-CCNN | 0.0275 | 0.065 | 0.97 | 0.019 |
| Proposed method | 0.0121 | 0.0066 | 0.98 | 0.017 |

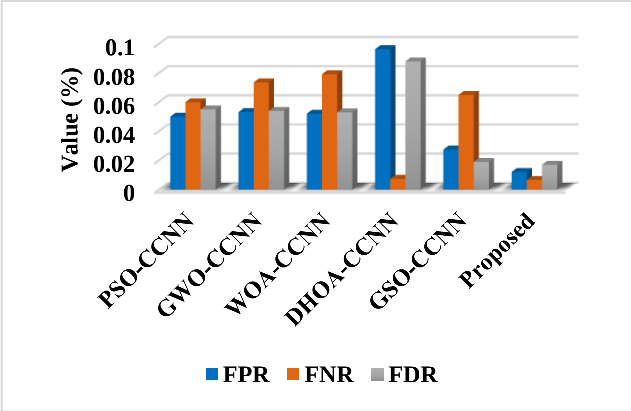



**Fig 6.** Comparison-based false predictions

The typical deep learning algorithms employed in the smart healthcare frameworks for heart disease prediction are validated and compared in Table 6 and Fig. 7 by these two figures. Similar to this, Table 7 and Fig 8 compare and evaluate the precision, F1-score, and Matthews Correlation Coefficient (MCC) for the same deep learning algorithms. Additionally, the dataset related to heart disease used for the false prediction study is displayed in Table 8 and Fig 9. The suggested DOS-Care architecture offers significantly better outcomes when compared to the other current approaches, according to the overall comparison study using the heart disease dataset. Since, the BB-HH based feature reduction, KHO based loss function estimation and GDRCNet based disease classification are the major reasons for obtaining improved performance results in the proposed system.

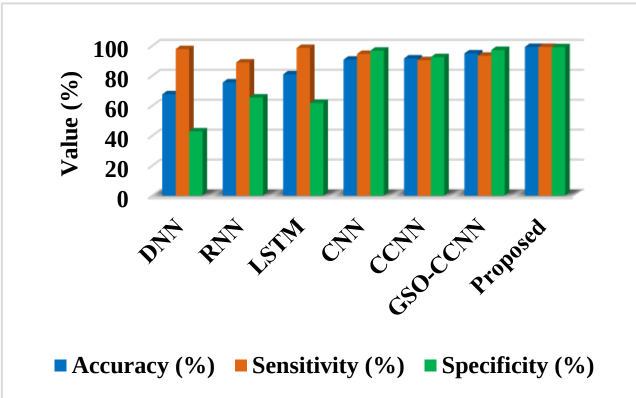



**Fig 7.** Performance comparison with standard deep learning techniques using heart disease dataset

**Table 6.** Comparison with other deep learning techniques

| *Methods* | *Accuracy (%)* | *Sensitivity (%)* | *Specificity (%)* |
|---|---|---|---|
| DNN | 67.67 | 97.88 | 42.94 |
| RNN | 75.58 | 88.90 | 65.52 |
| LSTM | 80.98 | 98.65 | 61.83 |
| CNN | 90.85 | 94.62 | 96.84 |
| CCNN | 91.58 | 90.5 | 92.5 |
| GSO-CCNN | 94.99 | 93.48 | 97.25 |
| Proposed method | 99.3 | 99.3 | 99.1 |

**Table 7.** Prediction analysis with standard deep learning techniques

| *Methods* | *Precision (%)* | *F1-Score (%)* | *MCC (%)* |
|---|---|---|---|
| DNN | 58.39 | 73.15 | 47.18 |
| RNN | 66.05 | 75.79 | 54.57 |
| LSTM | 73.68 | 84.31 | 65.70 |
| CNN | 88.42 | 91.41 | 81.85 |
| CCNN | 91.13 | 90.81 | 83.04 |
| GSO-CCNN | 98.07 | 95.72 | 89.83 |
| Proposed method | 99.1 | 99 | 99.1 |

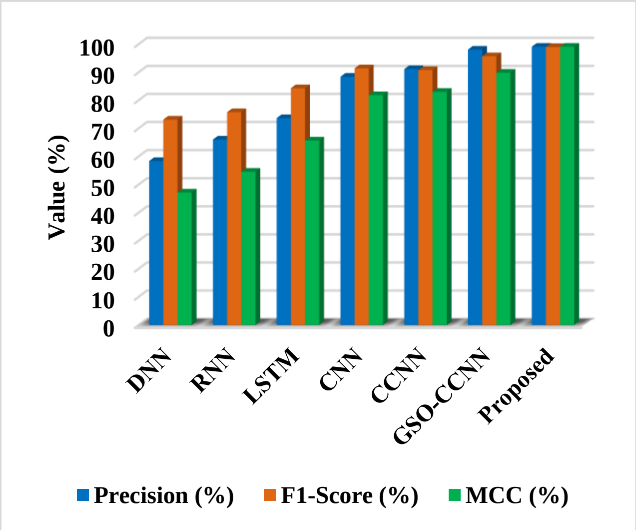



**Fig 8.** Precision, F1-score and MCC using heart disease dataset

**Table 8.** False detection analysis with standard deep learning techniques

| *Methods* | *FPR* | *FNR* | *NPV* | *FDR* |
|---|---|---|---|---|
| DNN | 0.570 | 0.021 | 0.4294 | 0.211 |
| RNN | 0.344 | 0.110 | 0.655 | 0.339 |
| LSTM | 0.381 | 0.013 | 0.618 | 0.263 |
| CNN | 0.131 | 0.053 | 0.868 | 0.115 |
| CCNN | 0.075 | 0.095 | 0.925 | 0.088 |
| GSO-CCNN | 0.027 | 0.065 | 0.972 | 0.019 |
| Proposed method | 0.0121 | 0.0066 | 0.98 | 0.017 |

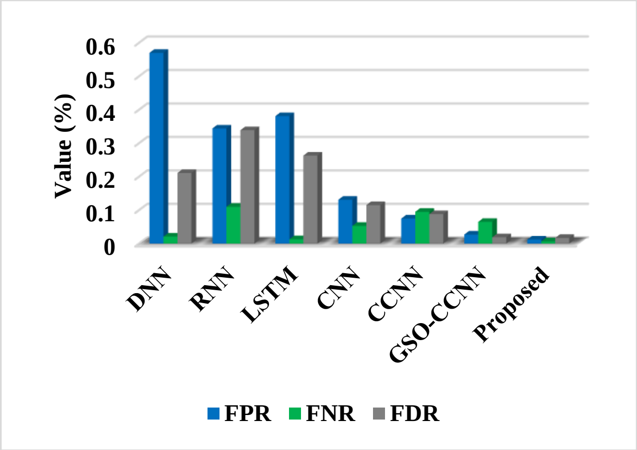



**Fig 9.** False detection analysis with standard deep learning techniques using heart disease dataset

Additionally, as shown in Table 9 and Fig 10, the performance of the suggested DOS-Care framework is also validated and compared using the PIMA diabetes dataset. Then, as shown in Table 10 and Fig 11, some error measures, including RMSE and MAE, are verified and contrasted for the existing and suggested models. These findings also show that the suggested DOS-Care offers effective results by accurately identifying the disease type with minimal error rates.

**Table 9.** Comparison with machine learning techniques using PIMA dataset

| *Methods* | *Precision (%)* | *Recall (%)* | *Accuracy (%)* |
|---|---|---|---|
| SVM | 81.9 | 71.8 | 71.8 |
| LR | 73.8 | 73.8 | 73.7 |
| MLP | 77.7 | 77.7 | 77.6 |
| RF | 73.8 | 73.8 | 73.7 |
| DT | 74.8 | 74.8 | 74.8 |
| NB | 80.4 | 80.5 | 80.4 |
| Ensemble DL | 83.5 | 83.5 | 83.5 |
| Proposed method | 99.2 | 99.1 | 99.2 |

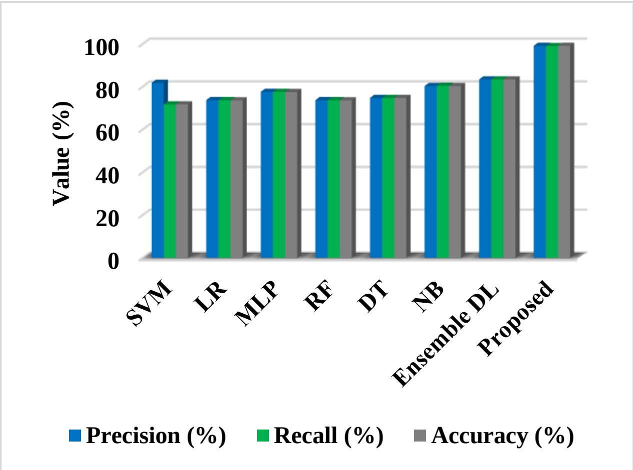



**Fig 10**. Comparative analysis using PIMA dataset

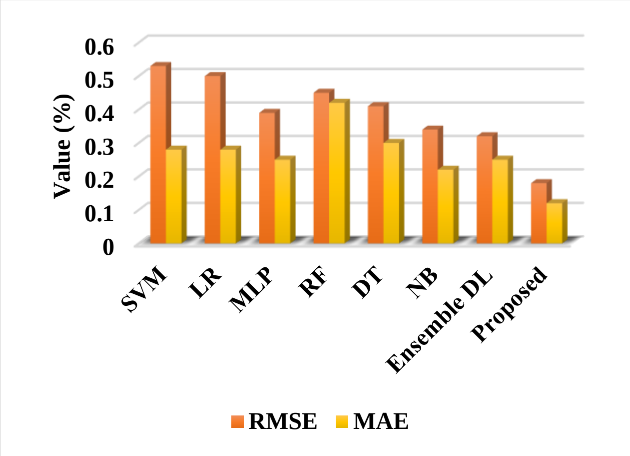



**Fig 11.** Error rate analysis using PIMA dataset

**Table 10.** Error analysis

| *Methods* | *RMSE* | *MAE* |
|---|---|---|
| SVM | 0.53 | 0.28 |
| LR | 0.50 | 0.28 |
| MLP | 0.39 | 0.25 |
| RF | 0.45 | 0.42 |
| DT | 0.41 | 0.30 |
| NB | 0.34 | 0.22 |
| Ensemble DL | 0.32 | 0.25 |
| Proposed method | 0.18 | 0.12 |

## 5. Conclusions

The original contribution of this study is the use of cutting-edge mining techniques in conjunction with IoT technology to build the Deep Optimized Smart Healthcare (DOS-Care) system, which predicts diabetes and heart disease. In the suggested work, a patient's medical record obtained through IoT sensors is considered as input, and an AI technique is used to carry out the disease diagnosis to give patients with diabetes and heart disease the correct medications. In this paper, a DOS-Care paradigm for disease prediction is developed using the PIMA, Cleveland, and Alizadeh datasets. The provided data has undergone preprocessing to remove any unnecessary information, such as unbounded or negative ratings. In this work, feature extraction has been used to gather statistical features like variance, mean, standard deviation, and entropy. After the pertinent features have been retrieved from the dataset, the BB-HH optimization technique is utilized to reduce the number of features needed for accurate classification. The proposed DOS-Care system can detect both diabetes and heart disease, and the accompanying medical datasets are vast. The GRDCNet classifier is then used to precisely identify the disease type from the patient's medical information after feature reduction. Because the main objective of this study is to use a cutting-edge DOS-Care architecture to diagnose and recognize both diabetes and heart disease. Moreover, the KHO technique is used to optimally compute the loss function of a classifier to make an effective prediction with high accuracy. The outcomes of performance evaluation are validated and contrasted using a variety of metrics. The overall comparison research utilizing the heart disease dataset shows that the proposed DOS-Care architecture gives significantly superior outcomes when compared to the other existing techniques. The main factors in the proposed system's enhanced performance outcomes include the BB-HH based feature reduction, KHO based loss function estimate, and GDRCNet based disease classification. The current work can be extended in future by applying a new IoMT framework for the identification and diagnosis of different chronic diseases.

## List of abbreviations

IoT – Internet of Things
BB-HH - Boosted Binary Harris Hawks
DOS-Care - Deep Optimized Smart Healthcare
GRDCNet - Gated Recurrent Deep Convolutional Network
KHO - Krill Herd Optimization
IoMT - Internet of medical things
ANN – Artificial Neural Network
CNN – Convolution Neural Network
PSO - Particle Swarm Optimization
WHO - World Health Organization
CSO - Crow Search Optimization
LSTM - Long Short Term Memory
AI – Artificial Intelligence
ML - Machine Learning
DL – Deep Learning
AFO - Artificial Flora Optimization
FDNN - Fuzzy Deep Neural Network
RNN - Recurrent Neural Network
GRU - Gated Recurrent Unit
RMSE - Root Mean Square Error
MAE - Mean Absolute Error
TN – True Negative
TP – True Positive
FN – False Negative
FP – False Positive
MCC - Matthews Correlation Coefficient
DNN - Deep Neural Network
CCNN - Convolutional Capsule Neural Network
SVM - Support Vector Machine
LR - Logistic Regression
MLP - Multilayer Perceptron
RF - Random Forest
DT - Decision Tree
NB - Naive Bayes
FPR - False Positive Rate
FNR - False Negative Rate
NPV - Negative Predictive Value
FDR - False Discovery Rate

# Declarations

### Availability of data and material

The popular diabetes dataset known as PIMA and heart disease datasets including Cleveland, and Z-Alizadeh datasets have been used in this study.

### Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

### Funding

No funding was received to assist with the preparation of this manuscript.

### Authors Contributions

The author **USN** Contributed and put effort on paper to Organize the Paper. Also technically contributed to data analysis and involved in the Background study of the Paper and helped the mathematical derivations. **RSG** involved in the Background study of the Paper and helped the mathematical derivations and technically contributed and made English Corrections and grammar checking. All the authors have read and approved the manuscript.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