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An Intelligent IoT Framework for Heart Diseases Prediction Using Harris Hawk Optimized GRNN

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Abstract

Recently, Heart diseases is considered as the one of deadliest diseases which has resulted in the increased death rates across the globe. Predicting heart diseases requires vast experiences along with advanced knowledge. IoT and AI are two emerging technologies that help in heart disease prediction. High diagnostic accuracy with minimal processing overhead, however, continues to be a design problem for researchers. To address this problem, this paper develops the Intelligent IoT structure for the better prediction of cardiac diseases employing Harris Hawk Optimized Gated Modified Recurrent Units (HHO-M-GRU). The paper also proposes the real time data collection using IoT wearable test beds which comprises of electrocardiography sensors (ECG) interfaced with MICOTT Boards & ESP8266 transceivers. For later processing, the acquired data are saved on the cloud. The proposed deep learning network is utilized for evaluating the received heart data and used for predicting the heart diseases. Additionally, the suggested HHO-GRU is trained with the versatile datasets which consist of normal and abnormal stages of heart diseases. By calculating the suggested model's performance measures, including accuracy, precision, recall, specificity, and F1-score, a thorough experiment is conducted. The proposed framework was implemented in Keras libraries with Tensorflow 2.1.1 as backend. Furthermore, prediction performance and complexity overhead is compared using the other cutting-edge deep learning algorithms already in use to demonstrate the model's superiority. in predicting the heart diseases. The suggested approach beats previous models for learning with respect to of accurate prediction (99%) and minimal computing overhead, according to the results.

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Keywords: Internet of Things; AI; Harris Hawk; Gated Recurrent Units (GRU); MICOTT boards

1. Introduction

Smart Health care system has changed the face of diagnosis by incorporating the disruptive technologies includes IoT, AI & 5G networks [1,2]. Integrating these technologies into medical devices enhances the diagnosis and treatment process. This brings undisputed advantages for people suffering from the grave diseases such as heart failures, and individuals needing stable monitoring and management [3-5].

In the smart health care system, IoT is utilized to collect the essential data from the patients and updates medical practitioners about the severity of diseases within a standard time of time interval. Additionally, IoT-based remote medical surveillance systems care for the health of older individuals who choose to remain at home and do not want to jeopardize their comfort [6–8]. IoT plays vital role in patient monitoring system while artificial intelligence improvises the diagnosis and treatment process [9-12]. Researchers from all over the world are working on smart applications including mobile medical services, health-aware advice, as well as smart health care systems because of the IoT as well as being used in the healthcare sector. [13-17]. Though IoT and AI changed the face of health care monitoring and treatment process, predicting the heart disease remains to be complex task among the clinicians and researchers. Patients with heart disease do not experience symptoms until the very end stages of the disease, at which point it is already too late as the damages are irreparable. Several learning models, including CNN [18], RNN [19], and LSTM[20], have been utilized in the past for the prediction of heart diseases but lacks in high performance due to its computational complexity.

Hence the primary motivation of this work is to create a model for predicting heart disease that high accuracy sacrificing computational overhead. The proposed research provides the intelligent framework for better prediction heart diseases that employs both IoT & deep learning algorithms. The proposed framework consists of two important phases such as data collection unit and prediction phase. The real time IoT test beds are used in the first phase whereas Optimized Gated recurrent neural networks are proposed in second phase.

The following is the work's contribution: The research's primary contribution is to the framework design, which plants the seeds for a less complex system of heart disease prediction. The framework develops the IoT architecture for real time data collection which consists of ECG sensors, microcontrollers, ESP8266 transceivers, gateways, and AWS cloud servers. Secondly, optimized gated recurrent gates (GRU) are developed for the prediction of cardiac disease. Finally, the extensive evaluation is carried out by calculating the performance metrics of the suggested algorithm and contrasted with other existing works.

The following describes the way the paper is organized: The relevant works that multiple writers have proposed are presented in Section II. In Section-III, procedures including data pre-processing and the suggested hybrid model are given. In Section-IV, the dataset descriptions, experiments, conclusions, and analysis are presented. Section-V, the paper's conclusion, offers suggestions for further improvement.

2. Related Work

S. Farzana utilized AI models such as SVM, RF, KNN, Gaussian Naïve Bayes & Xg-Boost for the health care monitoring. The main advantage of this framework is, Accuracy is calculated through all five AI algorithms and improved through percentage. Heart disease prediction in a short amount of time. Random forest has an accuracy rate of 88.52%. at the same time main limitation is Accuracy for predicting the heart disease have reached around 96% above using ML algorithm [**21].**

M. S. Raja utilized Random Forest methodology for the health care monitoring. The main advantage of this framework is it has High execution and exactness rate and it is entirely adaptable and high paces of accomplishment are accomplished. Not only are ML applications for disease prediction as well as diagnosis used, but also in the fields of radiology, bioinformatics, and medical imaging diagnosis, among others. This framework struggles when the dataset size is increased **[22].**

M. A. Alim used Stratified KFold and Random Forest algorithms for the healthcare monitoring. This framework outperformed the Hoeffding tree method's reported accuracy of 85.43%, achieving accuracy of 86.94%. But major drawback of this framework is Naive Gradient Booting which is still untouched the infield of vascular heart **disease [23].**

A. Ed-Daoudy utilized big data for health care monitoring. The suggested work is executed using the Spark platform, which incorporates the Random forest algorithm and its two stages of & Live data streams, on just one node cluster with an 8GB RAM Core i7 CPU running Linux. The prediction model's sensitivity, specificity, & accuracy are calculated and evaluated. The performance of the framework degrades when it is handled with heterogeneous data **[24].**

To monitor healthcare, R. Atallah & A. Al-Mousa used an ensemble model. The Ensemble model outperformed all individual classifiers in accuracy, with a rate of 90%. Clinicians can use the model to study patient scenarios to validate their diagnoses and lessen human error. The classifier's default parameters were used for the first test, which resulted in an accuracy of 80%. However, this methodology has a significant flaw in that it degrades as dataset sizes grow [25].

M. R. Ahmed incorporated the cloud computing for the health care monitoring. This framework utilized ANN model. According to the analysis's findings, the ANN performed the best overall with regard to of accuracy, specificity, and sensitivity. This framework's main drawback is that it takes more time for training and testing of the real time data [**26].**

A. Pandiaraj incorporated Machine learning algorithm- SVM, Random Forest, HRFLM and Linear strategy (LM),GA for the health care monitoring. The selection Tree and theory for an extra increment by using hereditary calculation to reduce the relevant information to get a perfect set of quality that is suitable for predicting cardiac illness. By integrating the qualities of RF and Linear method, the projected 0.5 breed HRFLM strategy is used (LM).HRFLM determines whether or not the user is being extremely accurate in their prediction of coronary poor health. The limitation of this framework is it requires large computational resources when handling the real time data **[27].**

J. P. Li utilized methodologies such as SVM, FCMIM for the effective health care monitoring framework. (FCMIM) can be applied to develop a highly intelligent system to detect heart disease using a classifier support vector machine. The proposed diagnosis system (FCMIM-SVM), when compared to previously described methods, achieved good accuracy. The effectiveness of a method based on machine learning For HD identification, FCMIMSVM outperforms Deep Neural Network. The main limitation of this framework, the performance of the entire framework is degraded when it is tested under real time data **[28**].

Q. He utilized ML algorithms in an IoT environment for the efficient health care monitoring. The best way to continually track and forecast patient ECG data obtained from IoT sensors while retaining adequate prediction accuracy was clearly determined by this approach. This framework had a 90% accuracy rate for predicting cardiac disease but main constrain is error rate is not achieved [29].

M. Ganesan incorporated cloud computing for the health care monitoring. According to the simulation results, the J48 classifiers outperform other classifiers with regards to accuracy, precision, recall, F-score & kappa value. But the major constrain of this work is it require preprocessing of data to maintain the same performance without performance degradation [**30]**.

3. Proposed Framework

The three basic steps of the proposed framework are (i) data collection, (ii) data pre-processing, and (iii) classification and prediction. Figure 1 displays the suggested framework's block diagram.

The Harris Hawk optimized Gated recurrent neural networks can be used in the suggested framework to predict the patient's cardiac illness. The algorithm goes through training and testing to produce an accurate prediction. The system is trained using the suggested model on three separate datasets from UCI, Public Health, and Framingham. Testing is conducted utilizing IoT devices after training. These Internet of Things (IoT) gadgets are fastened to the patients which transmit sensor values continuously. These are anticipated based on training results, and the suggested model contrasts the values to produce classified results. The training phases' steps are described below.

3.1 Materials And Methods:

The suggested machine learning model can be used to forecast the patient's cardiac illness in the given framework. This system requires testing and training to implement this method. The proposed study uses three datasets for evaluation and training, including the Framingham Heart Study, Public Health Dataset, and UCI Machine Learning Repository. Table I gives the descriptions of datasets use for training. After training, data from the IoT sensors are directly given to the system for diagnosing the heart disease prediction.

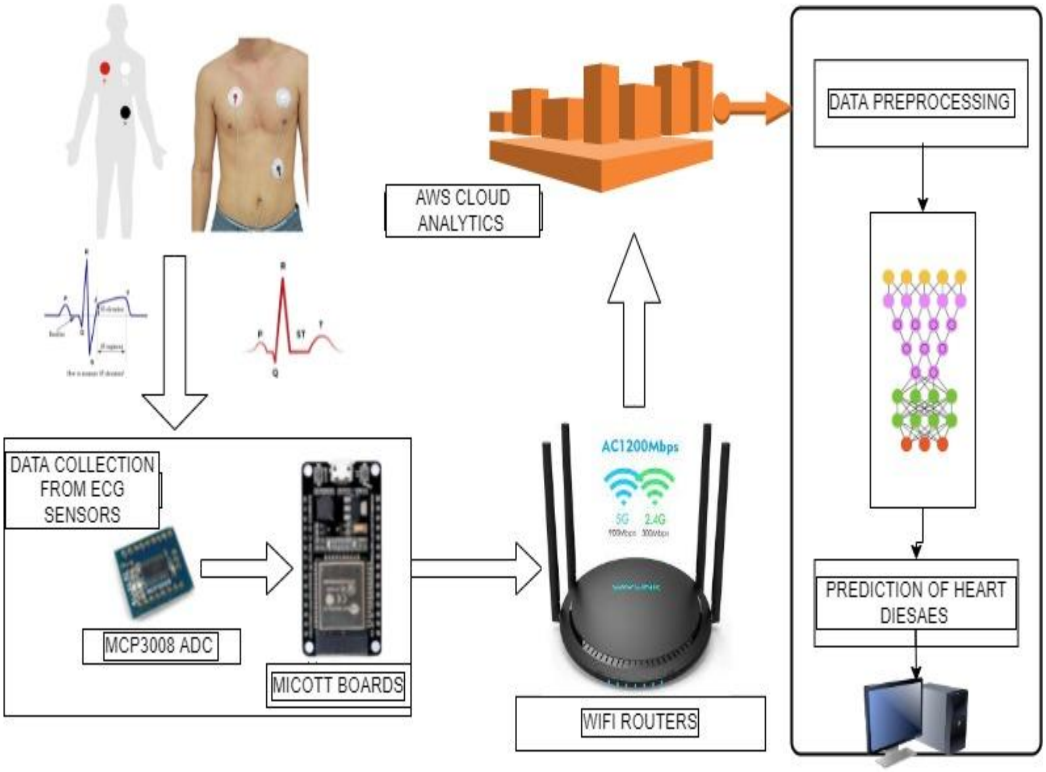


Figure 1: Overall Block Diagram for the Proposed Framework

Table 1: Description of the datasets employed for the experimentation

Dataset Description	No of data	No of records	No of Attributes	Associated Tasks
UCI Machine Learning respiratory	18902	303	75	Classification
Public health Datasets	3479	1025	14	Prediction
Framingham	4000	4000	16	Prediction

To assess the effectiveness of the suggested model, nearly 42 volunteers with age group ranging from 40 to 65 were selected. Nearly 50% of participants are normal and 50% of participants are mean to have the heart diseases. This research work uses IoT for collecting the ECG signals from the volunteers. The positioning of IoT devices onto the individuals is shown in Figure. The primary Internet of Things (IoT) devices for collecting ECG data are MICOTT boards, which have an 8-bit NODEMCU as its main CPU and interface with 10-bit SPI (Serial Peripheral Interfaces) driven MCP3008 analog channels and ESP8266 WIFI transceivers. These boards are used to collect the ECG sign also from the subjects and stores it in the AWS cloud for further testing. The IoT boards are powered with the 3.3V batteries and can be replaced with the other batteries when it is drained out. Besides, the ECG data collection, blood pressure of the patient is also measured which will be used as the reference values to fulfill the missing values at the pre-processing stage. Table II shows that total number of data

Table 2: Real time data Used for the Testing and Evaluation

Dataset Description	No of data	No of records	No of Attributes	Associated Tasks	Training Data /Testing
Real Time Datasets	1290	236	18	Classification	70; 30

3**.2 Data Preprocessing**:

The three processes of data preprocessing included in this research project are separation, redundancy elimination, and replacement of missing values. By examining the patients' age and blood pressure, the value that is missing of a specific attribute is replaced. These two parameters are taken as reference values which are considered as the indirect impact on the heart diseases. Next step is reduction of data by eliminating the duplicated attributes. The patients are finally divided depending on the categories of chest pain, such as 1) usual angina 2) unusual angina

3.3 Propsoed Training Model:

After pre-processing data, Harris Hawk optimized GRU is used for the prediction of heart diseases from the patients. The detailed explanation of the GRU is presented in preceding section. The suggested training model for predicting heart disease is shown in Figure.

3.3.1 Gru Network:

LSTM version GRU is thought to be the most fascinating. The goal of this concept, which was put forth by Chung et al. [31], is to integrate the forget gate with input vector into a single vector. Both long-term sequences and long memories are supported by this network. When compared to the LSTM network, the complexity is drastically reduced.

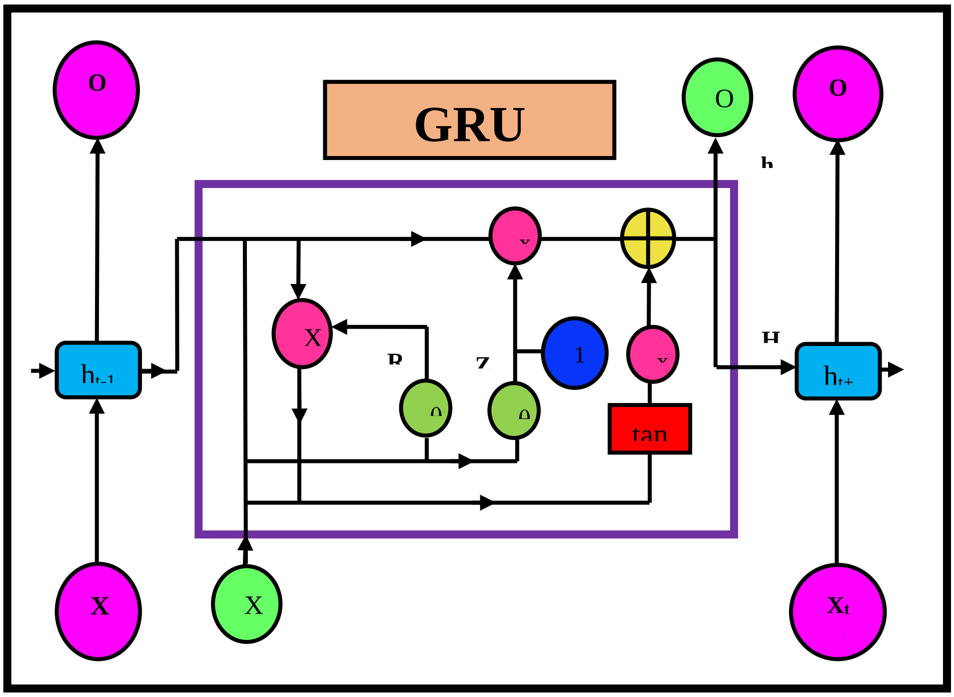


Figure 3: GRU -network Architecture

Chung developed the following equations to illustrate the traits of GRU.

$h_t = (1 - x_t) \odot h_{t-1} + x_t \odot h_t$ (1)

$\widetilde{h_t} = g(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h)$ (2)

$z_t = \sigma(W_h x_t + U_z h_{t-1} + b_z)$ (3)

$r_t = \sigma(W_h x_t + U_r h_{t-1} + b_r)$ (4)

The equation that represents the entire GRU characteristic $P = GRU(\sum_{t=1}^{n}[x_{t,} h_{t,} z_{t,} r_t(W(t), B(t), \eta(tannh))]$ (5)

Where xt ⇨ “input feature at the present state” , yt ⇨ “output state” , ht ⇨ “output of the module at the present instant”, Zt & rt ⇨ “ update & reset gates “, W(t) ⇨ “weights” ,B(t) ⇨ “bias weights at present instant”. With the preprocessed ECG data, these GRU networks are utilized to obtain the temporal properties. To prevent over-fitting issues, the model with the GRU trains the R-R interval maxima with bigger changes and use the Harris Hawk approach to maximize the weights given to the GRU.This study employs a modified GRU to address the complexity issue, with the gates tweaked using weights from the prior state and bias information.

3.3.2 Harris Hawk Algorithm

The HHO algorithm was inspired by the various ways that hawks hunt and attack their prey. The three steps of HHO, a population-based optimization technology, are exploration, transformation of exploration, & exploitation. Figure 4 displays the various HHO stages.

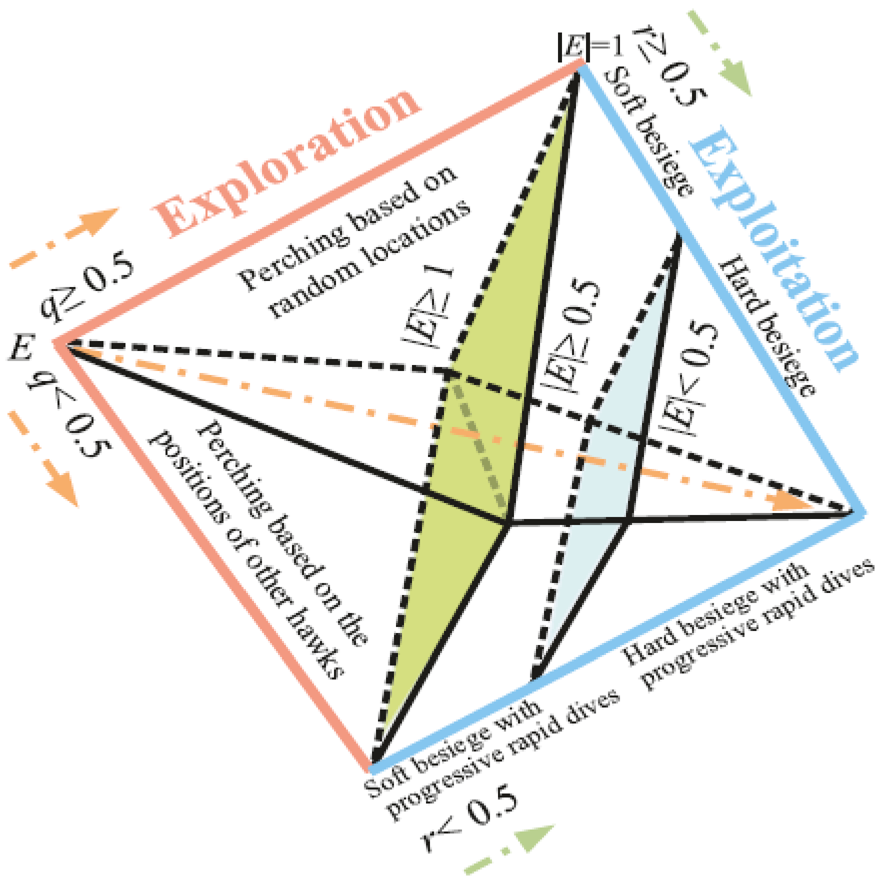


Figure 4: Different HHO phases

3.6.1. Exploration Phase

At this point, hawks perch in arbitrary locations dependent on the locations of other members or rabbits, which are represented as follows:

$$X(t+1) = \begin{cases} X_{rand}(t) - r_1 |X_{rand}(t) - 2r_2 X(t)|, & q \geq 0.5, \\ (X_{rabbit}(t) - X_m(t)) - r_3(LB + r_4(UB - LB)), & q < 0.5, \end{cases} \quad (6)$$

$$X_m(t) = \frac{1}{N} \sum_{i=1}^{N} X_i(t), \quad (7)$$

Where $X(t+1)$ ⇨ "the new position of hawks in the next iteration", $X_{rabbit}(t)$⇨ "position of prey", & $X(t)$ ⇨ "position of hawks". The absolute amount of the elements is indicated by the modulus. r_1, r_2, r_3, r_4 & q ⇨ " random numbers [0, 1]". **UB** & **LB** ⇨ "upper & lower bounds of variables". $X_{rand}(t)$ ⇨ "position of a random hawk population". $X_m(t)$ ⇨ "average location of the current population of hawks".

3.6.2 Transformation of Exploration & Exploitation

The following equations are used to assess the transition phase, which takes into account the prey's escape energy:

$$E_1 = 2\left(1 - \frac{t}{T}\right), \quad (8)$$

$$E = E_0 E_1, \quad (9)$$

Where t ⇨ "current iteration"; E_0⇨ "initial energy of a prey [-1,1]", & T ⇨ "maximum number of iterations".

2.3. Exploitation Phase

At this moment, the hawks attack the victim using its attempts to flee and four different pursuit techniques. A successful capture necessitates the presence of escaping energy (E) as well as the potential of escape (r).

Hawks executed a mild besiege in the below equations where $r \geq 0.5$ and $|E| \geq 0.5$, meaning the prey has ample energy but fails to escape:

$$X(t+1) = \Delta X(t) - E|JX_{rabbit}(t) - X(t)| \quad (10)$$

$$\Delta X(t) = X_{rabbit}(t) - X(t) \quad (11)$$

Where $\Delta X(t)$ ⇨ "contrast between the position of hawks at iteration t & the current position of prey" and $X_{rabbit}(t)$⇨ " the leap strength that changes randomly at each Iteration". r_5 ⇨ "random number [0,1]".

Hawks apply a strong besiege upon prey that has little escaping energy and the prey is unable to escape, as shown by $r \geq 0.5$ and $|E|< 0.5$, according to the following model:

$$X(t+1) = X_{rabbit}(t) - E|\Delta X(t)| \quad (12)$$

Hawks hunt through a more intelligent soft encirclement known as soft besiege with progressive quick dives when $r < 0.5$ and $|E| \geq 0.5$. This behavior is depicted as follows:

$$Y = X_{rabbit}\ (t)0_v - E\ |X_{rabbit}\ (t) - X(t)|, \quad (13)$$

$$Z = Y + SXLF\ (D), \quad (14)$$

Where D ⇨ " problem's dimension", S ⇨ "random vector of size $1 \times D$", and **LF** ⇨ "Levy flight function" as

$$LF\ (d) = 0.01 \times \frac{u \times \sigma}{|v|^{1/\beta}}, \quad (15)$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times sin\ \pi\ \beta/2}{\Gamma(1+{\beta}/{2}) \times \beta \times 2^{\beta - 1/2}} \right)^{1/\beta}, \quad (16)$$

Where u, v ⇨ "random normal distribution vector with the size of $1 \times d$", β ⇨ " constant and bound to a value of 1.5 ", and Γ ⇨ "standard Gamma function". The hawk's positions can be updated by modelling

$$X(t+1) = \begin{cases} Y\ if\ F(z) < F\big(X(t)\big), \\ Z\ if\ F(z) < F\big(X(t)\big), \end{cases} \quad (17)$$

A hard besiege is initiated when the prey's energy is exhausted ($r < 0.5$ and $|E| < 0.5$). Equations (18) & (19) serve as a model for calculating Y and Z. The procedure for updating is as follows:

$$Y = X_{rabbit}\ (t) - E|JX_{rabbit}\ (t) - X_m\ (t)|, \quad (18)$$

$$Z = Y + S \times LF(D) \quad (19)$$

$$X(t+1) = \begin{cases} Y\ if\ F(z) < F\big(X(t)\big), \\ Z\ if\ F(z) < F\big(X(t)\big), \end{cases} \quad (20)$$

3.3.4 PROPOSED MODEL - HYPERPARAMETER OPTIMIZATION

As mentioned in Section 3.4.4, the weights of GRU's dense networks are optimized using the straightforward Harris Hawk techniques. The main phrase employed in this instance to optimize the weights and concealed layers of GRU is the Harris Hawk reflection mechanism. These hyperparameters are initially chosen at random and sent to the GRU trained networks. Equation (21) provides the fitness function for the proposed network. Hyperparameters are determined for each iteration using equation (20). Whenever the fitness function and equation (21) agree, iteration ends.

$$\boldsymbol{Fitness\ Function\ = Average\ \{Max(Accuracy) + Max\ (Precision) + Max(Recall)} \quad \textbf{(21)}$$

After the Harris Hawk algorithm has optimized the input weights, the suggested classification layer quickly and efficiently distinguishes between normal and cardiac disease. Algorithm-1 presents the suggested classification layers' operational mechanism. Table III uses the specification of the training the proposed model. Hence the Modified GRU is used to extract the R-R intervals followed by the Harris Hawk Optimized Dense Classifier networks for an effective identification of cardiac diseases. Figure 5 shows the complete architecture of proposed model.

Steps	**Algorithm-1 // Pseudo code for the suggested model**
01	Bias weights, concealed layers, epochs, as well as learning rate are the inputs.
02	Target : Prediction of Normal/Heart Diseases
03	Bias weights, concealed layers, epochs, as well as learning rate should be assigned at random.
04	Set the three parameters
05	Start the while loop
06	Use equation (5) for calculating the results from GRU cells.
07	Apply equation (21) to the FF to determine it.
08	Start the for loop to its maximum
09	Apply equations (6) and (7) to assign the bias values & input layers.
10	Apply equation (21) to FF calculation.
11	Check for (FF equal to threshold)
12	jump step 17
13	otherwise
14	Jump step 08
15	Halt
16	halt
17	Check for (output <=1)
18	//Normal ⇨determined
19	Otherwise check for(output <=2&& >1)
20	// heart disease ⇨1 determined
21	Otherwise check for(output <=3&& >2)
22	// heart disease ⇨2 determined

23	otherwise
24	Jump step 09
25	Halt
26	Halt
27	halt

Table 3: Optimized Training Parameters

Sl.no	Detailed specifications	Parameters
01	No of Epochs	200
02	Size of the batch	50
03	Rate of learning	0.0001
04	Training sample	70
05	Testing sample	30

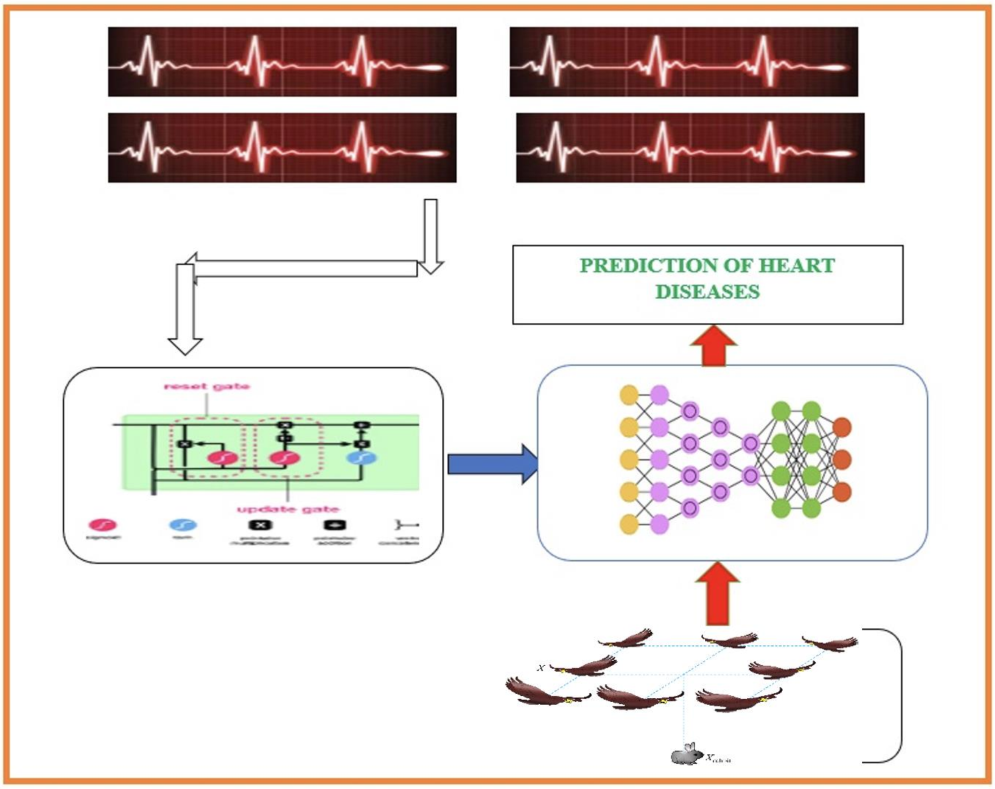


Figure 5: Working Architecture of the Proposed Harris Hawk Operated GRU Training Network

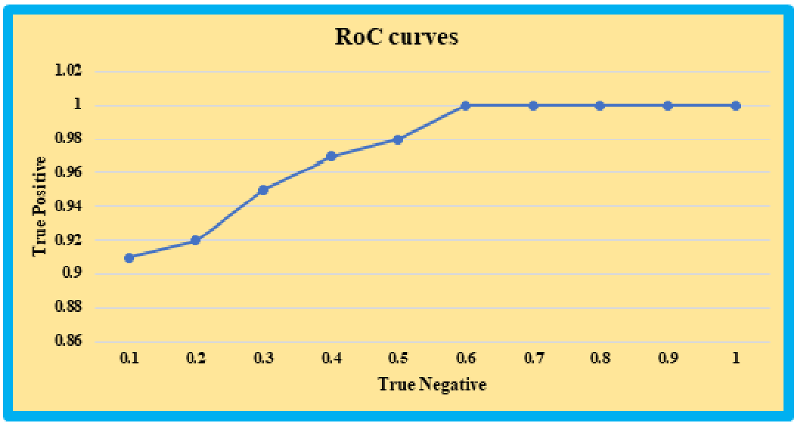
4. Experimental Results

The proposed model was implemented in PC workstation with i9 CPU, 240 GB SSD, NVIDIA Titan V4 and 3.2 GHZ Python using Keras Libraries and Tensorflow v 2.1 as backend. The model was evaluated using statistics namely accuracy, precision, recall, specificity & F1-score. The mathematical expression used for calculating the performance metrics is presented in Table IV. We also computed the AUC and confusion matrix to demonstrate the superiority of the suggested model. To solve the overfitting along with generalization issues, early halting is used. When the proposed model's validation performance shows no progress over a sustained period, this procedure is utilized to end the iteration. To address the issue of class imbalance, training and testing make use of an even distribution of data. Table IV provides the mathematical formula for computing the performance measures used to assess the suggested model.

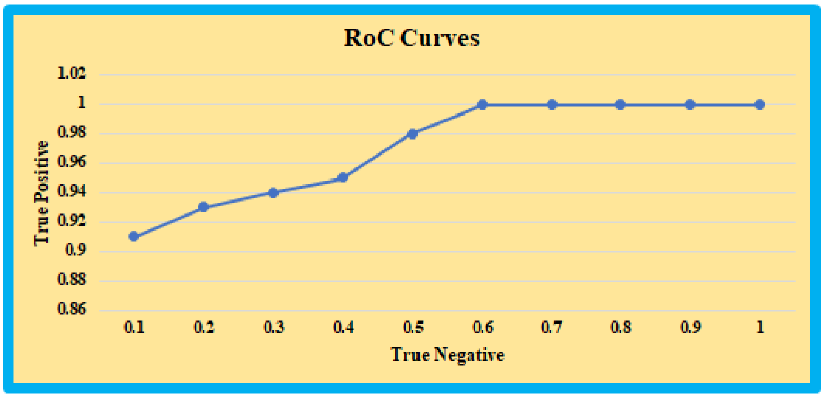
Table 4: Performance Metrics used for the Evaluation

Sl.no	Performance Metrics	Equations
01	Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
02	Recall	$\frac{TP}{TP+FN}$ x100
03	Specificity	$\frac{TN}{TN+FP}$
04	Precision	$\frac{TN}{TP+FP}$
05	F1-Score	$2.\frac{Precison * Recall}{Precision + Recall}$

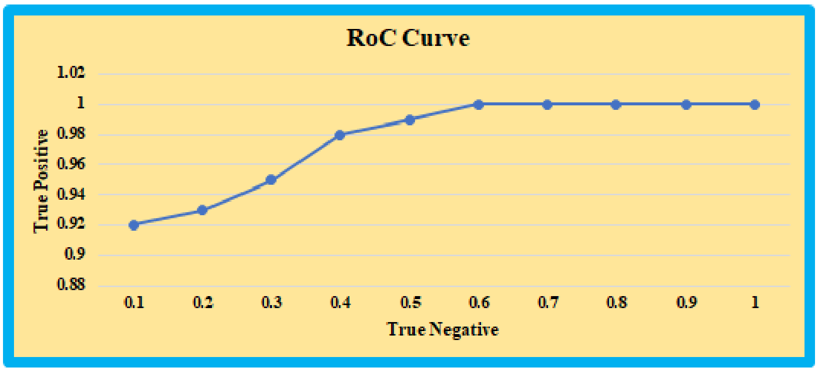
TP & TN ⇨ "True positive & True negative", FP & FN ⇨ "False positive & False negative"



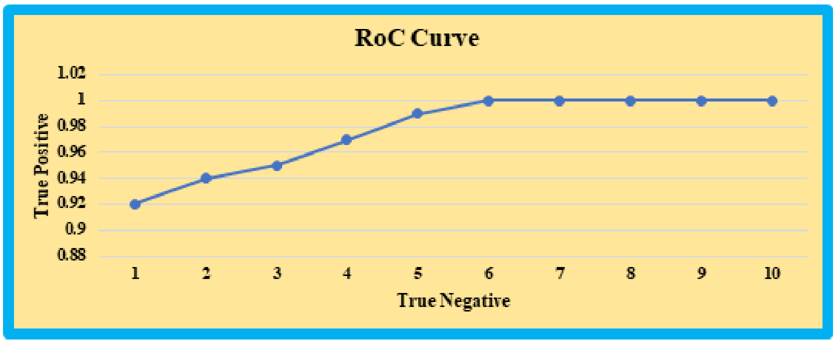
(a)



(b)



(c)



(d)

Figure 6: ROC curves a) UCI datasets b) Framingham c) Public Datasets c) real time Sensor inputs

ROC curves to the suggested approach with various datasets and real-time datasets are shown in Figure 6(a)-(d). With the ROC curves, Area Under Curves (AUC) are calculated for each dataset. It is found that AUC is 1.0 for UCI, 0.975 for Firmingham, 1.0 for public datasets and importantly 1.0 for real time dataset**.**

Label	Normal	Heart Disorder
Normal	98.5%	1.2%
Heart Disorder	1.3%	98.6%

Figure 8: Confusion matrix for the suggested structure in detection of Normal and Heart Disorders.

The effectiveness metrics of the suggested framework is assessed for the different number of epochs. Figure 7–10 displays the effectiveness of the suggested model in handling the UCI respiratory datasets. Figures 7-10 shows the suggested model' metrics in handling the Framingham and Public health datasets. The statistics clearly show that the suggested model has provided the highest accuracy for 200 epochs of 99.94% accuracy, 99.91% precision, 99.91% recall, 99.91 specificity, & 99.91% F1-score.

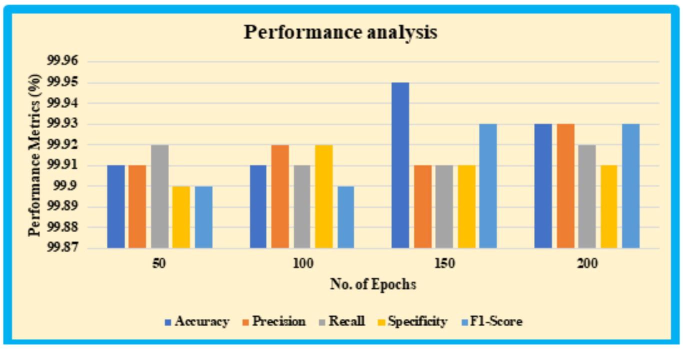


Figure 7: Performance metrics of proposed model utilizing the UCI Datasets

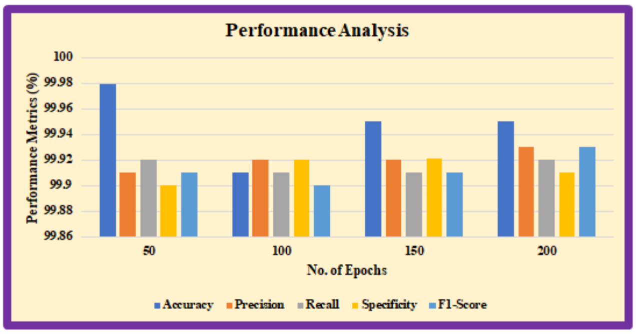


Figure 8: Performance metrics of proposed model utilizing the firmangham datasets

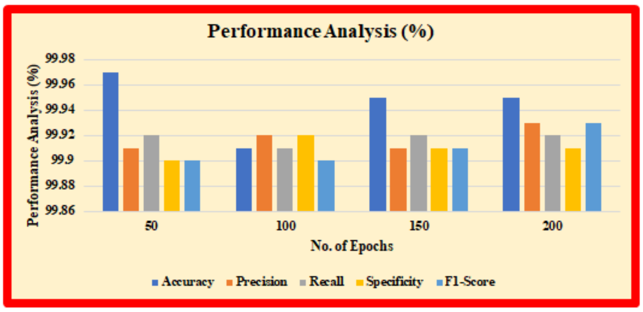


Figure 9: Performance metrics of proposed model utilizing the public health datasets

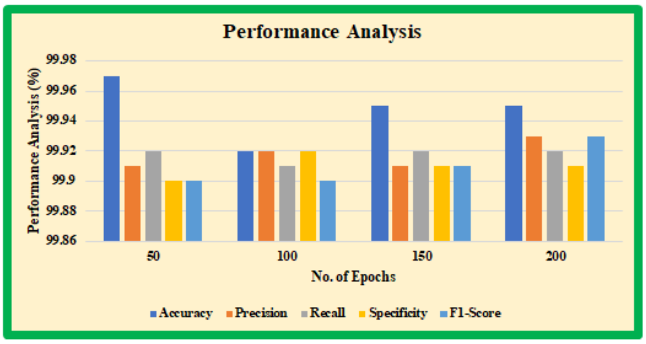


Figure 10: Performance metrics of proposed model utilizing the real time sensor datasets

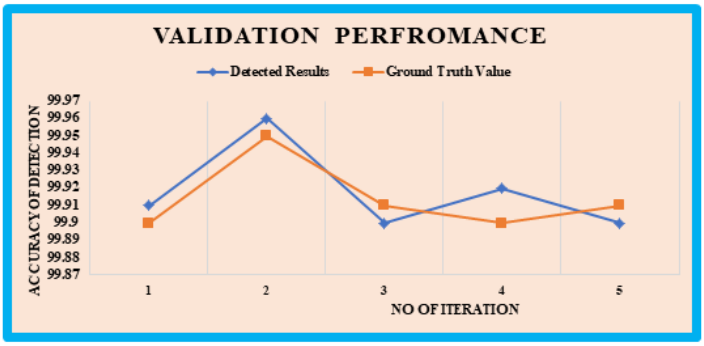


Figure 11: Evaluation curves for the suggested model for the detecting the normal conditions for the 15 subjects

The suggested model's validation performance is shown in Figures 11–14 for the real time data from the IoT sensor testbeds. It is evident from the Figure 11-14; suggested framework has shown the similar fashion of performances as presented in Figures. From the above evaluation, the model that was suggested is demonstrated to handle the real time data as same the training datasets. Also, the predicted values are validated with ground truth scenario in which the suggested approach has produced the RMSE of 0.0023 as compared with ground truth patients. It is evident from the figures 11-14 proposed predictor has produced maintains the uniform performance for the increased subjects. It has been demonstrated that the suggested model provides consistent results while dealing with big subjects. Furthermore, it is proved that the error between the ground truth and predicted values is found to be low, which find its suitability the better prediction of heart diseases.

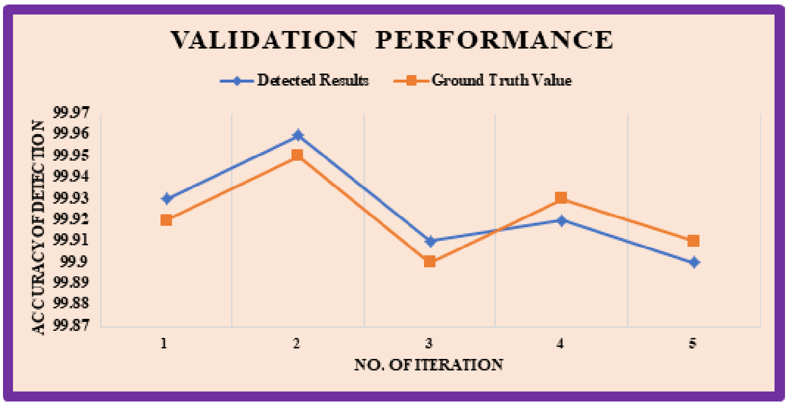


Figure 12: Evaluation curves for the suggested model for the detecting the heart conditions for the 15 subjects

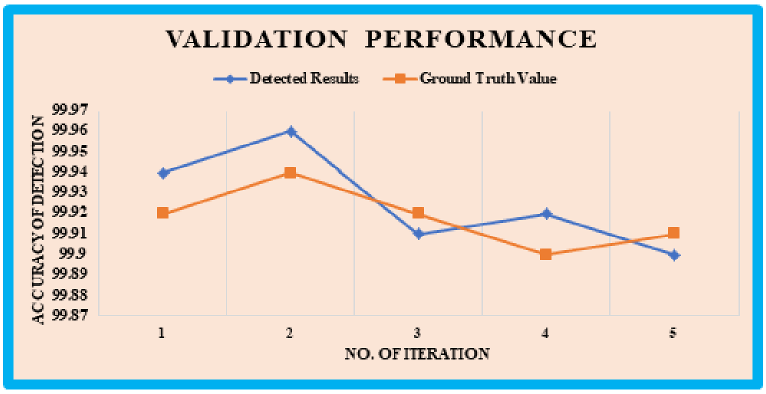


Figure 13: Evaluation curves for the suggested model for the detecting the normal conditions for the 30 subject

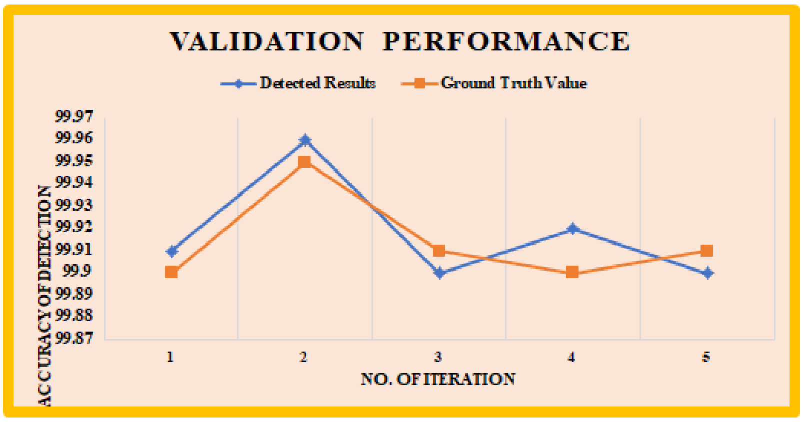


Figure 14: Evaluation curves for the suggested model for the detection of heart conditions for the 30 subjects

The suggested predictor is being compared with state-of-the-art options that are like this framework to demonstrate the superiority of the model that was suggested. Tables V through VIII present a comparison of the results of the various algorithms when applied to various datasets. The similar state of art works which are included for the comparative studies are LSTM [19], CNN+LSTM[20], RNN+LSTM[33], HRFLM[32], RFRS[31] and MDCNN[35].

Table 5: Comparative analysis of the distinct algorithm in handling the UCI datasets

Slno	**Algorithms**	**Performance Metrics**				
		Accuracy	Precision	Recall	Specificity	F1-Score

01	LSTM	92.3%	91.4%	91.2%	90.2%	90.3%
02	CNN+LSTM	92.5%	92.34%	92.48%	92.35%	92.6%
03	RNN+LSTM	93.4%	94,7%	94.0%	94.2%	94.0%
04	HRFLM	90.0%	90.9%	90.78%	90.68%	91%
05	RFRS	87.4%	88.2%%	88.4%	88.43%	88.2%
06	MDCNN	96.2%	96.2%	95.9%	95.5%	95.35%
07	PROPOSED MODEL	99.93%	99.93%	99.92%	99.91%	99.93%

Table 6:Comparative Analysis of the Different Algorithm in Handling the Framingham datasets

Slno	**Algorithms**	**Performance Metrics**				
		Accuaracy	**Precision**	**Recall**	**Specificity**	**F1-Score**
01	LSTM	92.3%	91.4%	91.2%	90.2%	90.3%
02	CNN+LSTM	92.5%	92.34%	92.48%	92.35%	92.6%
03	RNN+LSTM	93.4%	94,7%	94.0%	94.2%	94.0%
04	HRFLM	90.0%	90.9%	90.78%	90.68%	91%
05	RFRS	87.4%	88.2%%	88.4%	88.43%	88.2%
06	MDCNN	96.2%	96.2%	95.9%	95.5%	95.35%
07	PROPOSED MODEL	99.95%	99.93%	99.92%	99.91%	99.93%

Table 7: Comparative Analysis of the Different Algorithm In Handling the Public health datasets

Slno	**Algorithms**	**Performance Metrics**				
		Accuaracy	**Precision**	**Recall**	**Specificity**	**F1-Score**
01	LSTM	92.3%	91.4%	91.2%	90.2%	90.3%
02	CNN+LSTM	92.5%	92.34%	92.48%	92.35%	92.6%
03	RNN+LSTM	93.4%	94,7%	94.0%	94.2%	94.0%
04	HRFLM	90.0%	90.9%	90.78%	90.68%	91%
05	RFRS	87.4%	88.2%%	88.4%	88.43%	88.2%
06	MDCNN	96.2%	96.2%	95.9%	95.5%	95.35%
07	PROPOSED MODEL	99.95%	99.93%	99.92%	99.91%	99.93%

Table VIII Comparative Analysis of the Different Algorithm In Handling the Real time Datasets

Slno	Algorithms	Performance Metrics				
		Accuaracy	**Precision**	**Recall**	**Specificity**	**F1-Score**
01	LSTM	92.3%	91.4%	91.2%	90.2%	90.3%
02	CNN+LSTM	92.5%	92.34%	92.48%	92.35%	92.6%
03	RNN+LSTM	93.4%	94,7%	94.0%	94.2%	94.0%
04	HRFLM	90.0%	90.9%	90.78%	90.68%	91%
05	RFRS	87.4%	88.2%%	88.4%	88.43%	88.2%
06	MDCNN	96.2%	96.2%	95.9%	95.5%	95.35%
07	PROPOSED MODEL	99.95%	99.93%	99.92%	99.91%	99.93%

The effectiveness of the different approaches in handling the various datasets is shown in Tables VI–VII. It is evident from the tables, proposed model and MDCNN has produced the similar fashion of performance for predicting the heart diseases from different datasets. But the proposed model which works on the Harris Hawk Optimized Hyperparameters of the GRU has edged over the MDCNN in predicting the heart diseases. In other hand, LSTM, HRFLM, CNN+LSTM (average performance of 90%) has also achieved the considerable moderate performances whereas RFRS has attained the lowest performance (average performance of 87.4%) in predicting the heart diseases. Table VIII displays the comparison of the various algorithms in predicting the heart diseases utilizing the real time IoT test beds. As found in previous case, the suggested model has performed better than the competing learning models. in predicting the heart diseases.

4.2 Complexity Analysis

To reduce the complexity of the suggested framework, has been incorporated the Modified GRU integrated with the Harris Hawk optimization technique. The complexity of the model has been calculated by using mathematical expression(22)

$$Complexity - Analysis\big(C(a)\big) = Nof\ GRU\ networks * \ No\ of\ Inputs\ \ dimensiona(22)$$

Table IX shows the computational parameters estimated for the different models and compared with the existing models.

Table 8: Different models' computational complexity for n-dimensional ECG signals

Sl.no	No of algorithms	No of Parameters estimated
01	LSTM	[4x(n^2+nm+n) * n]
02	GRU	[4nm*n]
03	MDCNN	2x(n^2+nm+n) * n]
04	Proposed Model	[2nm*n]

From the above table IX, it is found that the complexity of the proposed model consumes only 50 % lesser than LSTM, 30% less than the traditional GRU and even 40% less than MDCNN. The mode of training the network along with the optimization technique has resulted in the less computational overhead as in comparison with alternative learning models

6. Conclusion

IoT with AI has been utilized effectively in health care industry in detecting the various diseases particularly in predicting the chronic heart diseases. By conducting prompt examinations, these intelligent prediction systems have the potential to save many lives, particularly when patients are found in remote locations. Several methods are adopted to forecast cases of cardiac disease. This research work proposed the Intelligent prediction System with integration of IoT system and heart disease predictions system using Harris Hawk Optimized GRU networks. The cardiac disease is predicted with various three techniques such as Data preprocessing, Feature extraction By GRU and Classification by Optimized Harris Hawk networks. To reduce the complexity in the algorithm, this paper uses the Modified GRU along with hyperparameter optimization by the Harris Hawk algorithm. The extensive experimentation has been carried and proposed model is trained with the Four different datasets such as UCI, Framingham, Public health and real time datasets. Experimental results demonstrated that the suggested model exceeded the other models currently in use. In the future, these algorithms needs more improvisation in optimization to handle larger clinical datasets.

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