Research Article

Intellectual heartbeats classification model for diagnosis of heart disease from ECG signal using hybrid convolutional neural network with GOA

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Abstract

Automatic heart disease detection from human heartbeats is a challenging and intellectual assignment in signal processing because periodically monitoring of the heart beat arrhythmia for patient is an essential task to reduce the death rate due to cardiovascular disease (CVD). In this paper, the focus of research is to design hybrid Convolutional Neural Network (CNN) architecture by making use of Grasshopper Optimization Algorithm (GOA) to classify different types of heart diseases from the ECG signal or human heartbeats. Convolutional Neural Network (CNN) as an artificial intelligence approach is widely used in computer vision-based medical data analysis. However, the traditional CNN cannot be used for classification of heart diseases from the ECG signal because lots of noise or irrelevant data is mixed with signal. So this study utilizes the pre-processing and selection of feature for proper heart diseases classification, where Discrete Wavelet Transform (DWT) is used for the noise reduction as well as segmentation of ECG signal and Grasshopper Optimization Algorithm (GOA) is used for selection of R-peaks features from the extracted feature sets in terms of R-peaks and R-R intervals that help to attain better classification accuracy. For training as well as testing of projected Heartbeats Classification Model (HCM), the Standard MIT-BIH arrhythmia database is utilized with hybrid Convolutional Neural Network (CNN) architecture. The assortment of proper R-peaks and R-R intervals is a major factor and because of the deficiency of apposite pre-processing phases like noise removal, signal decomposition, smoothing and filtering, the uniqueness of extracted feature is less. The experimental outcomes show that the planned HCM is effective for detecting irregular human heartbeats via R-peaks and R-R intervals. When the proposed Heartbeats Classification Model (HCM) was verified on the database, model achieved higher efficiency than other state-of-the-art techniques for 16 heartbeat disease categories and the average classification accuracy is 99.58% with fast and robust responses where the correctly classified heartbeats are 86,005 and misclassified beats is only 108 with 0.42% error rate.

Keywords Heartbeats Classification Model · Discrete Wavelet Transform · Convolutional Neural Network · Grasshopper Optimization Algorithm · R-peaks and R-R Interval Analysis

1 Introduction

Heart ailment advancements because of inadequate blood deliver to the human heart whereas coronary artery disease matures or arrhythmias are cruel and elongated permanent [1]. As indicated by insights from the Centers for Disease Control and Prevention (CD-CP), coronary illness is the world's driving reason for death. Therefore, early analysis of cardiovascular malady is significant for diminishing the staggering effect and expanding personal satisfaction [2].

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A widespread heart-monitoring electronic device which is used toanalyze the cardiac arrhythmia that continuously collectsthe ECG signals of human in the whole day (24 h). Artificial Intelligence (AI) basedheart-monitoring modelhas also been developed to categorize ECG signalsinto common and irregularpatterns using human heartbeats by training as well astesting with standard MIT-BIH Arrhythmia database [3] which publically available on PhysioNet.

AI or deep learning is a sub-field of machine learning approaches, and it targets to study ECG signal structures from multi hierarchical layers to resolve the multifaceted tasks that were problematic for the traditional neural network-based model [4].However, AI or deep learning-based heart-monitoring simulations for categorizing ECG heartbeats wouldstumble uponhitches in over-training initiated by quasi-periodic activities of the ECG signal [5]. Thus, this one isessential to exploit the number of samples held in an ECG heartbeats section for demonstrating input variables to evadeover-training. So in this research,firstly a means of defining thepeak number of ECG heartbeats sections utilized to encrypt the input variables proposed which is shown in Fig. 1. After that, we construct anoptimized Convolutional Neural Network (CNN) based on Grasshopper Optimization algorithm (GOA) [6, 7] by way of amending initiation elements to classify ECG heartbeats into 16 diseases categories (15 arrhythmias and 1 normal) like Premature Ventricular Contraction (PVC), Right Bundle Branch Block (RBBB), Left Bundle Brunch Block (LBBB) Normal Heartbeats, Atrial Premature Contraction (APC), etc. [8].

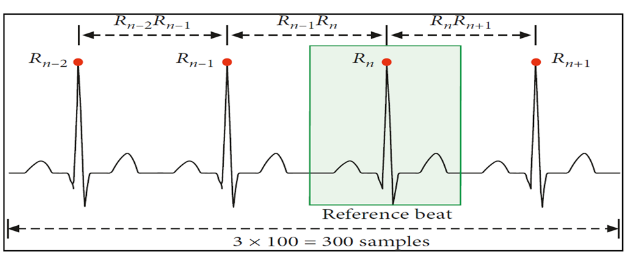

Fig. 1 ECG Signal Segments

ECG heartbeats peaks and intervals determination is represented in Fig. 1. To conclude the numeral of ECG heartbeats models for providinginput ECG facts, we outline R-peak and R-R intervals features of ECG signals as follows:

***R_n*:**It is the reference heartbeat in which the n[th] R-peak is denoted by a red dot.
***R_{n-k}*:**It is the previous R-peaks time position by way of respect to the R_n reference beat.
***R_{n+k}*:**It is the next R-peaks time position by way of respect to the $R_n$reference beat.
$R_{n-k} \times R_{n+k}$: It is the R-peak interludeamid the time locations of R_{n-k} peak and R_{n+k} peak.

Figure 2 presents the proposed block diagram which is used to heartbeats monitoring based on the optimized Convolutional Neural Network (CNN), as well as the proposed model, is known as Heartbeats Classification Model (HCM). For training and testing of proposed Heartbeats Classification Model (HCM), the Standard MIT-BIH arrhythmia database is utilized with hybrid Convolutional Neural Network (CNN) architecture [9]. Here, R-peaks, as well as R-R intervals,are used as ECG features and in Heartbeats Classification Model (HCM); feature extraction plays a significant responsibility to categorize masses of cardiac diseases (Fig. 3). The used heartbeats samples are given in Table 1.

1.1 Motivation and contributions

ECG signal is a type of non-stationary signals and it is broadly used to monitor the heartbeats rate and their tuning. The main purpose of this exploration is to provide an academic diagnosis exemplary which can aid in human operating AI or deep learning and swarm optimization algorithms in ECG heartbeats classification [10]. As the number of death surges day by day because of heart complications and the central cause of this death is the absence of superior diagnosis exemplary accessibility. Starting these kinds of **perplexing jobs** we

Fig. 2 Proposed Block Diagram

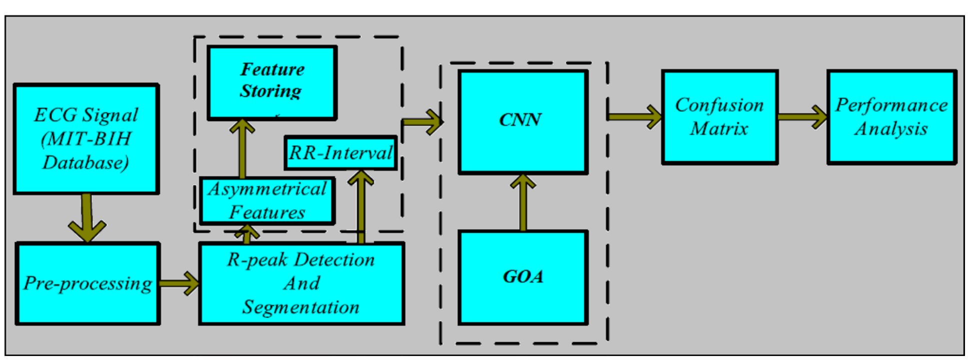

Fig.3 Steps of proposed HCM

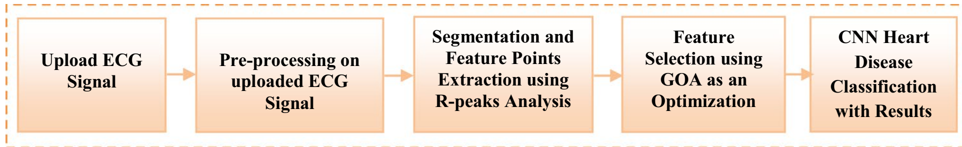

Table 1 MIT-BIH arrhythmia ECG data used in the proposed model

KC'G signal Type-Annotation	Total	Training	Test
Normal (NOR)–N	75,017	11,253	63,764
Left Bundle Branch Block (LBBB)–L	8072	2825	5247
Right Bundle Branch Block (RBBB)–R	7255	2520	4716
Atrial Premature Coturuction (APC)–A	25 16	K01	1655
Preventricular Contraction (PVC)–V	7120	24 < »	4634
Paced Beal (PACE)–P	702 t	2 158	4566
Aherralird Atrial Prcmatrirc Heal (AP)–a	150	75	75
Ventricular Flutter (VF)–!	472	236	236
Fusion of Ventricular and Normal Beat (VFN)–F	802	401	401
Blocked Atrial Premature Beat (BAP)–x	193	07	96
Nodal (Junctional Escape Beat)–j	229	115	1 14
Fusion of Paced and Normal Beta (FPN)–1	*1X2*	491	491
Ventricular Escape Beat (VE)–E	11)6	53	53
Nodal (Junctional) Premature Beat (NP)–J	XI	42	41
Atrial Escape Beat (AE)–e	16	8	8
Llnclassifkable Beat (UN)–Q	33	17	16
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present an academic Heartbeats Classification Model (HCM) for diagnosis of heart disease from ECG signal utilizing hybridization of Convolutional Neural Network (CNN) with Grasshopper Optimization Algorithm (GOA) [12, 14]. In simple verses, this paper marks the following offerings.

- We introduce a new ECG signal segmentation method centered on the combination of the smoothing technique along with the Discrete Wavelet Transform (DWT).
- For the classification of the ECG heartbeats into 16 heartbeats disease categories, the Convolutional Neural Network (CNN) classifier is used with the Grasshopper Optimization Algorithm (GOA) [15] feature selection algorithm with novel fitness function.
- For the authentication of introduced Heartbeats Classification Model (HCM), we estimate performance parameters of introduced work a like accuracy, error rate, sensitivity, and specificity with classification time and associate with state-of-the-art methods.

This paper demonstrates intelligent Heartbeats Classification Model (HCM) using a hybrid method by Convolutional Neural Network (CNN) using Grasshopper Optimization Algorithm (GOA) and its contrast with existing developments. The organization of this research article is given as:

- Specifically, in Segment 2, we illustrate the literate review (background survey) of previous work used for detection as well as segmentation of vascular configurations of skin lesions[13].
- The structural design of the recommended work is defined in Sect. 2.
- The simulation outcome is taken in Sect. 4.
- At last, we accomplish by way of discussions on presentchallenges as well as future trends in Sect. 5.

2 Litreture survey

In this section, we prefer the survey of old work centered on the ECG disease classification utilizing dissimilar algorithms and techniques. Sandeep Raj and Kailash Chandra Ray [1] had researched disease detection using Heart ECG Signal Analysis with a combination of Particle Swarm Optimization (PSO) Optimized Support vector Machine (SVM) and Discrete Cosine Transform (DCT). They present an innovative move toward medical science; using Discrete Cosine Transform (DCT) based pre-processing for effective exemplification of the heart ECG signal in time–frequency space with principal component analysis. In order to improve the disease classification rate, the Particle Swarm Optimization (PSO)[16, 19] method is working for gradually tuning the learning parameters of the Support Vector Machine (SVM) classifier with 16 classes of MIT-BIH arrhythmia database for the authentication of the work. Sasan Yazdani et al. [2] presented an analysis of heart rhythm classification. They used the concept of short-term ECG recording rhythms to classify the rhythm types. Features based on heart-rate variability model is presented and consider RR-intervals, and atrial/ventricular ECG morphologies as a feature of ECG signal and used ensemble classifier to categorize the ECG rhythm into different types like normal, other abnormal rhythms, fibrillation.T. Debnath et al. [3] had led a technique for examination of ECG signal and grouping of heart variations from the norm utilizing Artificial Neural Network [18, 21]. They utilized back-spread calculation with the idea of a feed-forward neural system for illness characterization of various heart classes. Three unique conditions for heart, for example, typical, bradycardia, and tachycardia are arranged impeccably however the square condition isn't accurately distinguished in work. Kumar et al. [4] had presented an integrated form of run-length encoding alongside the idea of bio-orthogonal wavelet transform so as to recognizing the QRS complex wave and henceforth reducing the size of the ECG information. The proposed model arrangement decreases the hardware cost up to 50% of the absolute expense and the experiment results have been performed on MIT-BIH arrhythmia dataset.

In view of the survey, we finish up some most important points which short out the existing problem of the heart illness characterization framework. The principle issue in ECG signal interpretation model is the disposal of undesirable commotion and artifact which can accomplish better accuracy of the framework [17]. Therefore, it is reasoned that signal filters are mandatory for the proposed model. The filters utilized in the previous works are directly utilized on the ECG heartbeats signals however right approach to utilize the filter with a blend of smoothing approach with a filtration system. A feature (R-peaks and R-R intervals) enhancement algorithm has not been utilized in the current work so for better feature choice, the use of stream lining is necessary to normalize the ECG heartbeats signals [20]. This mix in the proposed work accomplishes better characterization accuracy of proposed Heartbeats Classification Model (HCM) with quick and robust responses with ECG heartbeats signal.

3 Proposed methodology

The proposed an intellectual Heartbeats Classification Model (HCM) for diagnosis of heart disease from ECG signal utilizing the hybridization of Convolutional Neural Network (CNN) with Grasshopper Optimization Algorithm (GOA) system consists of fivemost important steps. Primarily, numerous signal pre-processing techniques will be functional to improve signal Excellency and apposite segmentation method will be put in to isolate out peaks from ECG signals. Here, to improve the signal quality, Discrete Wavelet Transform (DWT) based smoothing is used to minimize the unwanted noisy data from ECG signals. Then features will be extracted in terms of R-peaks as well as R-R intervals from the segmented ECG signaland apply feature selection using Grasshopper Optimization Algorithm (GOA). Moreover (if required) to feed such as input to the Convolutional Neural Network (CNN) typical to train and test Heartbeats Classification Model (HCM). At last, disease classificationhas been executed using Convolutional Neural Network (CNN) [22] exemplary to attain anticipated output for the automatic intelligent Heartbeats Classification Model (HCM).

The challenging task of this research work is to categorize the disease using ECG signalbased on thetraining of the system using Convolutional Neural Network (CNN) with Grasshopper Optimization Algorithm (GOA)[20].The following steps validate the variability of phases that need to be accomplished in the proposed Heartbeats Classification Model (HCM) model.

1. *Uploading ECG data*

   Upload ECG signal dataas of MIT-BIH arrhythmia database of 16 different classes. The uploaded native ECG signal is presented in Fig. 4 with a specific period.

   ECG heartbeats sample of humans is shown in Fig. 4 and the noise is present in the signal. So we need to

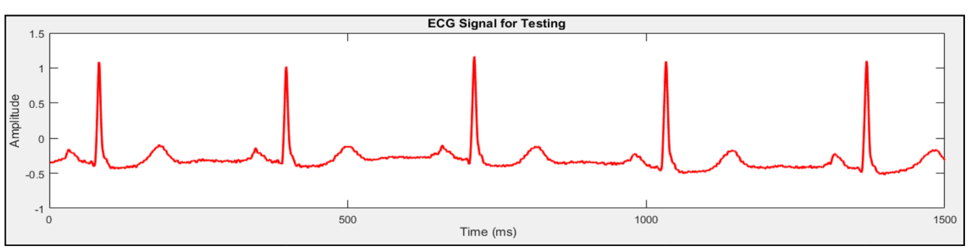

Fig. 4 Original uploaded ECG signal

reduce or minimize the noise level for further processing.

2. *ECG signal pre-processing*

Inthe proposed Heartbeats Classification Model (HCM) system, pre-processing steps are required as per the requirement to improve the signal quality. In the pre-processing stage, the transferred Electrocardiography (ECG) signal is processed so as to remove the clamor and undesirable signal which accomplishes better order accuracy of the framework. The most familiar commotion in ECG signal is the clamor because of the power line during recording. In this research work, the pre-processing comprises smoothing, De-noising utilizing Discrete Wavelet Transform (DWT) decay,and filtering of ECG signal. The pre-The pre-processing steps are described below for the proposed Heartbeats Classification Model (HCM) model.

3.1 Smoothing process

Signal smoothing is normally utilized to diminish the level of noise within the signal and creates a noise-free ECG signal with less bit value. In this proposed model smoothing process is done the concept of the estimation process. The smooth ECG signal is shown in Fig. 5 and the smoothing algorithm written as:

Algorithm 1: Signal Smoothing

Input of Algorithm: Original ECG Signal (S) and Estimate noise points (N)

Output of Algorithm: Smooth ECG Signal (S_M)

1. Determine the size of ECG Signal, S = S_z
2. For in range of S_z
3. Segmented ECG = Split signal in the structure of N
4. Calculate signal variation = Check neighbor peaks position and their variation in ECG signal
5. Estimate ECG Noise Level = Maximum variation
6. End
7. Smooth ECG Signal, S_M = Difference(S, Estimated Noise Level)
8. Return: S_M as Smooth ECG Signal
9. End

According to the signal smoothing algorithm, we have to build a smooth ECG signal such as specified in the below Fig. 5 which helps to reduce the noise level.

3.2 DWT (discrete wavelet transform)

After the smoothing process, we apply the Discrete Wavelet Transform (DWT) process for decomposition of the signal into 2 parts with different kinds of filters, for example, low pass filter as well as high pass filter. Discrete Wavelet Transform (DWT) returns the calculation and details coefficients of the ECG signal and the algorithm of Discrete Wavelet Transform (DWT) decomposition is written follows:

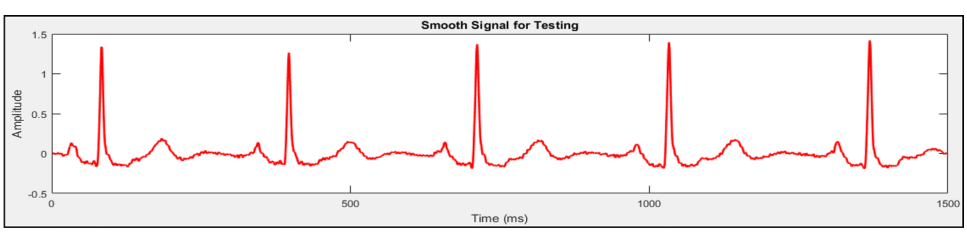

Fig. 5 Smooth ECG signal

Algorithm 2: DWT Decomposition

Input of Algorithm: Smooth ECG Signal (S_M), Level of Wavelet (N) and Family of Wavelet (Haar)
Output of Algorithm: Decomposed Coefficients (C, L) of Smooth ECG Signal

1.Find out the size of Smooth ECG Signal, $S_M = S_{MZ}$
2. Forin range of S_{MZ}
3.InitializeLPF& HPF
C = LFP(S_M, 2, N, Haar)
L = HFP(S_M, 2, N, Haar)
4. End
5. Return: Decomposed Factors (C, L) of Smooth ECG Signal
6. End

We have discovered the factors of a smooth ECG signal thataids to denoise the undesirable data from the ECG signal according to the Discrete Wavelet Transform (DWT) decomposition algorithm. The obtained coefficients of the ECG signalrepresented in Fig. 6 after processing using the Discrete Wavelet Transform (DWT) technique.

Figure 6 signifies the Discrete Wavelet Transform (DWT) factors of smooth ECG signal which is obtained once put onthe Discrete Wavelet Transform (DWT) decomposition algorithm. In Fig. 6 (a) represents the approximation coefficients of the ECG signal which is obtained by LPF and (b) signifies the details factors of ECG signal which is obtained by applying HPF. Obtained ECG signal coefficients are used in the filtering process of ECG signal and the filtering ECG is described in the below section.

3.3 Filtering of ECG signal

In the ECG signal filtering process, we have used the concept of thresholding method applied on smoothed ECG signal with Discrete Wavelet Transform (DWT) coefficients. Here, the thresholding method is applied to calculate the threshold level of noise by the smooth Electrocardiography (ECG) signal. The Electrocardiography (ECG) signal filtering algorithm is written as:

Algorithm 3: Filtering of ECG Signal

Input of Algorithm: ECG Signal Coefficients using DWT (C, L), Threshold point of noise in signal (T), Level (N) and Family of Wavelet (Haar)
Output of Algorithm: Filtered ECG Signal

1. Determine the size of C = S_C
2.Determine the size of L = S_L
3. For in range of S_C
4. For in range of S_L
5. Filtered ECG Signal = Filter (C, L, N, T)
6. End
7. End
8. Return: Filtered ECG Signal
9. End

The above-mentioned procedure of Electrocardiography (ECG) filtration is utilized to filter the uploaded original Electrocardiography (ECG) signal to act out the

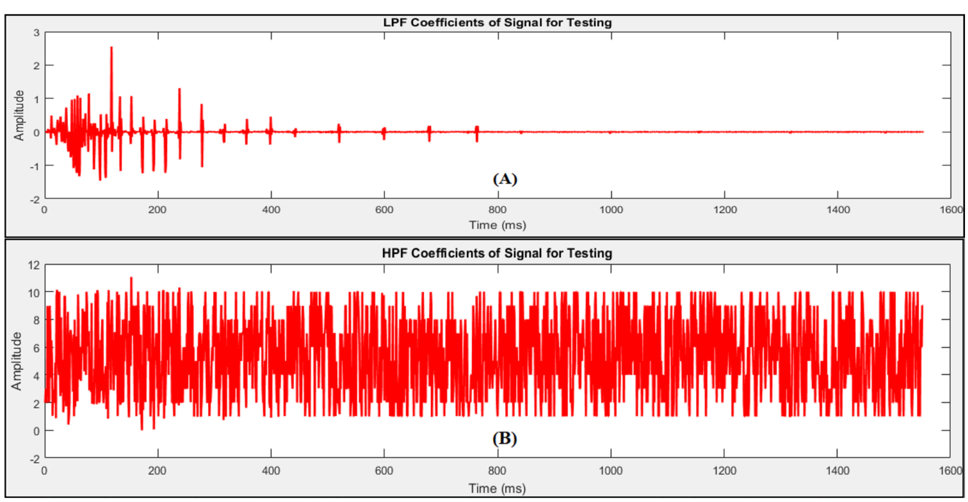

Fig. 6 **a** LPF and **b** HPF of DWT coefficients of smooth ECG signal

recommended Heartbeats Classification Model (HCM). After filtering, we have got a noise-free Electrocardiography (ECG) signal which is presented in Fig. 7.

Figure 7 describes the Electrocardiography (ECG) heartbeats signal [22] attained after applying the filtering method in presented Heartbeats Classification Model (HCM) to categorize the type of diseases. After this phase, Peaks analysis is applying to excerpt the features from filtered Electrocardiography (ECG) signals.

3.4 Feature analysis of ECG signal

After the pre-processing, we analyzed the feature pattern of the Electrocardiography (ECG) signal to find out the R peaks and their R-R intervals. To analyze and extraction of the R-peaks and R-R intervals, we have used below mentioned algorithm:

Algorithm 4: QRS-Peaks & Intervals Analyzer

Input of Algorithm: Pre-processed ECG Signal ($ECGSignal_P$)

Output of Algorithm: R-peaks& their R-R intervals

1. Find Peaks by way of their locations using
Peaks=Find peaks ($ECGSignal_P$)
2. Calculate theextreme peak value using Max peak = max (Peaks)
3. $Threshold\ of\ peaks\ (T_h) = \frac{(Max\ peak\ X\ 75)}{100}$(1)
4. Set count of R-peaks, Count= 1
5.Makea blank array to store R-peaks = []
6. For in range of all peak value
7. If Peaks $\geq T_h$ then
8. R-peaks (1, Count) =Location of Peaks
9.R-peaks (2, Count) = Value of Peaks
10. IncrementCount=Count+1
11. End
12. End
13. Calculated, R-R Intervals = Difference (Peaks (Next) - Peaks (Previous))
14. Return; R-peak of ECG Signal (R-peaks) with their intervals (R-R Intervals)
15. End

Based on the QRS-Peaks & Intervals Analyzer algorithm we find out the R-peaks as well as R-R intervals which are shown in Fig. 8.

With the help of the QRS-Peaks & Intervals Analyzer procedure, we have discovered the R-peak and their intervals in terms of Electrocardiography (ECG) signal features. The investigation of R-peak and their intervals are given

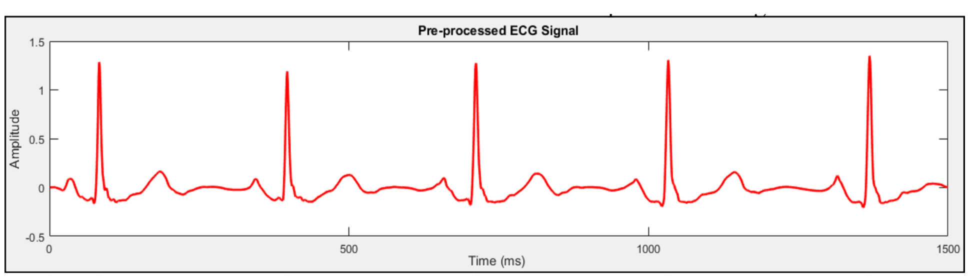

Fig. 7 Filtered ECG signal

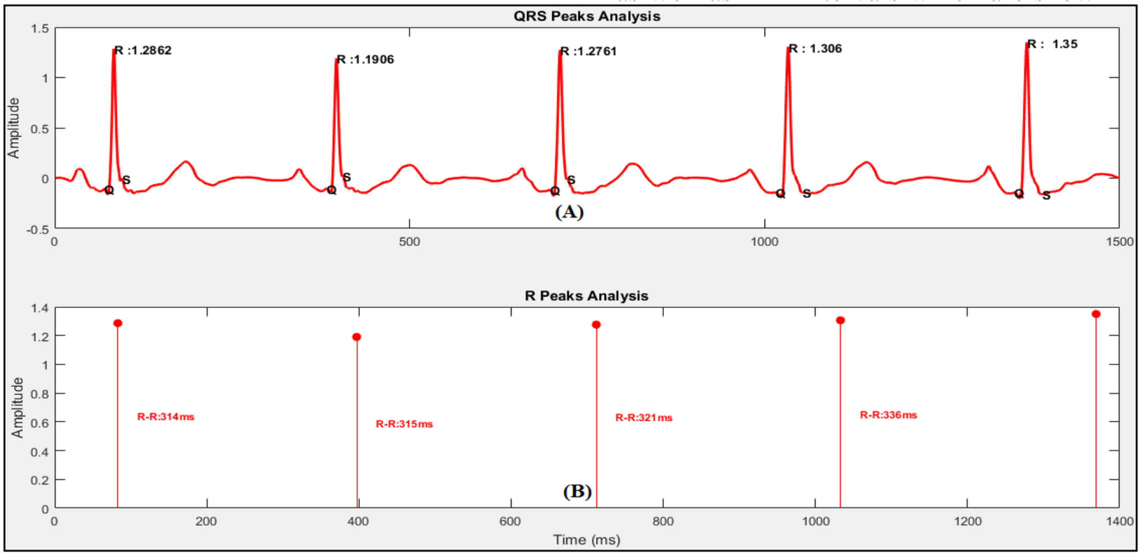

Fig. 8 QRS analysis of electrocardiography (ECG) signal

in Fig. 8a and b. In the graphical representation of peaks, the x-axis means the recording time in milliseconds and y-axis indicates the amplitude of Electrocardiography (ECG) heartbeats with QRS-peaks. Figure 8a represents the R-peaks with peak esteems and Fig. 8b represents R-R interval of Electrocardiography (ECG) signal and their worth is given between the two R-peaks. The R-R intervals of Electrocardiography (ECG) signal are determined to utilize the idea of differentiation among current and next R-peak. After the count of R-peaks and R-R intervals, we have to create a novel and ideal peak qualities has been discovered as the best feature, so we have utilized Grasshopper Optimization Algorithm (GOA) in proposed Heartbeats Classification Model (HCM) to optimize and choose the best and one of a kind feature sets for every sickness categories.

4 Feature selection using Grasshopper optimization algorithm (GOA)

Firstly we introduce the basic principle of Grass Hopper Optimization Algorithm (GOA) approach that is used for feature selection and it is inspired by the Swarm Intelligence (SI) techniques. Swarm Intelligence (SI) is one the most effective optimization algorithm architecture and used for feature selection. The behavior Swarm Intelligence (SI) technique is based on the grouped particle observation. Different types of behaviors are observed in nature and hence different algorithms are studied and presented like GOA, Particle Swarm Algorithm (PSO), Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), Cuckoo Search Algorithm (CSA), Firefly Algorithm (FFA), etc. GOA is one of the most popular algorithmic architectures of the Swarm Intelligence (SI) and it is utilized to optimize the features according to the fitness function which helps to select better features according to the ECG disease category. The algorithm of Grasshopper Optimization Algorithm (GOA) is written as:

Algorithm 5: GOA
Input of Algorithm: R-peaks&R-R intervals
Output of Algorithm: Optimized R-peaks&R-R intervals
1. Initialize the basic parameters of GOA
– Iterations for simulation (T)
– Number of Features as a Population (P)
– Lower Bound (LB) of selection
– Upper Bound (UB) of selection
– Fitness function for selection criteria
– Number of Selection (N)
2. Calculate the size of R-peaks&R-R intervals (R_s)
3. Set the fitness function of GOA:
$f(fit) = \begin{cases} False, & fs < ft \\ True, & fs \geq ft \end{cases}$ (2)
4. For in range of Rs
5. $fs = \sum_{i=1}^{Pop} f(i)$ (3)
6. $ft = \frac{\sum_{i=1}^{Pop} f(i)}{Lengthoffeature}$ (4)
7. f(fit) = fitness function which defines by equation (2)
8. Nvar = 1 // No. of variables to be selected
9. Opt_Peaks= GOA(P, Iterations, LB, UB, N, f (fit))
10. End
11. While T ~= Maximum
12. Optimized R-peaks and Intervals = Opt_Peaks
13. End
14. Return: Optimized R-peaks & R-R intervals
15. End

5 Classification using convolutional neural network (CNN)

Convolutional Neural Network (CNN) has been initialized for the classification of diseases using 2 phases, training and testing. The algorithm of Convolutional Neural Network (CNN) is written as:

Algorithm 6: CNN Model

Input of Algorithm: Optimized R-peaks & R-R intervalsas Training Data (T-Data), Categories of Disease as a Target (G) and Carrier of Signal Neurons (N)

Output of Algorithm: Trained CNN Structure

1. Make ready the basic CNN parameters
– Epochs/Iterations (E)
– Neurons/Carrier (N)
– Performance parameters: Cross-Entropy, Gradient, Mutation and Validation
– Training Algorithm: Scaled Conjugate Gradient (Trainscg)
– Data Division: Random

2. For in range of T-Data
3. If T-data belongs to Category (1) then
4. G (1, i) = True
5. Else if T-data belongs to Category (2) then
6. G (2, i) = True
.
.
.
7. Else If T-data belongs to Category (16) then
8. G (16, i) = True
9. End
10. End
11. Make ready the CNN using Training data and Target
12. Net = Pattern-net (T-Data, G, N)
13. Set the CNN training parameters according to the requirements and train the system
14. Net = Train (Net, T-Data, G)
15. Classification HCM Results = simulate (Net, Test ECG Feature)
16. If Classification HCM Results = True
17. Show classified results in terms of the heart disease
18. Compute the performance parameters of HCM
19. End
20. Return: Classified Outcomes
21. End

The architecture of the proposed CNN is given in the below Fig. 9.

Above Fig. 9 represents the CPU based CNN architectute used to train the proposed HCM for detection of heart diseases from ECG signal with different input, output and hidden layers (Fig. 10). The layers of CNN are given as:

Convolution map: In CNN, the convolution layer is a basic element and the objective of convolution is to extract features from the input image but in CPU based it is used for filtering the extracted feature by R-peak analysis. It consists of a group of learnable square filters which helps to find out the appropriate feature sets. Each filter is applied to the raw values of the ECG signal.

Max-pooling map: In the CNN architecture of proposed HCM, convolution layers are followed by sub-sampling layers and act as a unique feature extraction approach. A layer of max-pooling is an alternative of feature selection but in this work we used optimization techniques separately to increase the chances of feature uniqueness by using the GOA as an optimization technique. The output of max-pooling layer is passes to the classification model which is used as a maximum activation value and creates a structure of model.

ReLu function helps in faster training and addressed the vanishing gradient problem. After the training of Heartbeats Classification Model (HCM) using the proposed Convolutional Neural Network (CNN) algorithm, we have saved the trained configuration that is utilized in the categorization section to categorize the heart diseases as of the Electrocardiography (ECG) signal[11] with performance parameters.

6 Results and discussion

In this segment, the simulation outcomes of introduced Heartbeats Classification Model (HCM) using a hybrid method by Convolutional Neural Network (CNN) with GOA are deliberated and the effectiveness of introduced work is associated with an intelligent disease classification model with Particle Swarm Optimization (PSO)based Support Vector Machine (SVM) algorithm. The training and testing of the introduced Heartbeats Classification Model (HCM) is evaluated by MIT-BIH arrhythmia database of 16 different classes. By adapting the established proposed algorithms, the below consequences are computed with quality based parameters, such as accuracy, error rate,sensitivity, and specificity with classification time and compare with state-of-the-art methods [1].The performance analysis of proposed Heartbeats Classification Model (HCM) for each disease group of the event is estimatedby figuring quality-centered evaluation parameters suchas true positive (TP)/Original feature of testing, true negative (TN)/false feature with respect to

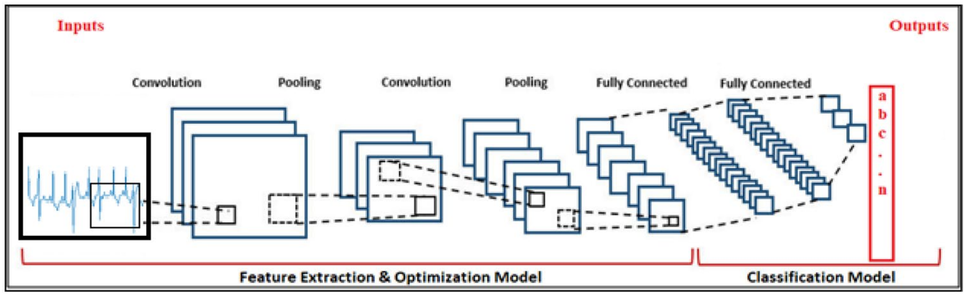

Fig. 9 CNN architecture of proosed HCM

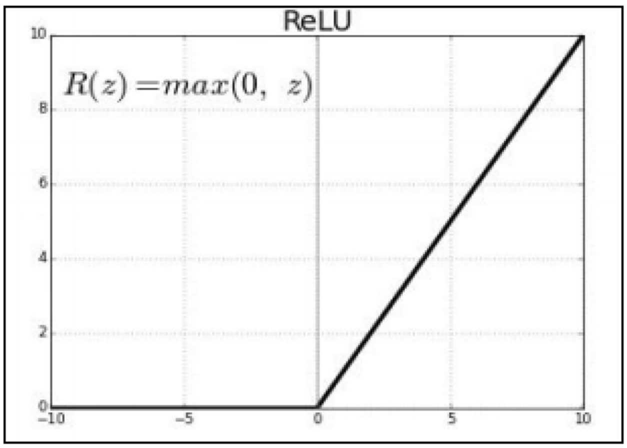

Fig. 10 CNN activation function

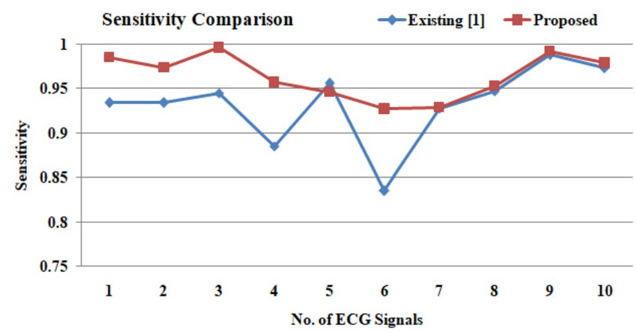

Fig. 11 Comparison of sensitivity

the training of Convolutional Neural Network (CNN), false positive (FP)/False feature during testing,and false negative (FN)/true feature for the training of Convolutional Neural Network (CNN) parameters, based onthese quality based parameters TP, TN, FP, FN, the performance metrics for each disease class of ECG signal are calculated. Here, in Table 2 of the confusion matrix, the column describes the computed heartbeats being categorized with introduced Heartbeats Classification Model (HCM) utilizing hybridization of GOA with Convolutional Neural Network (CNN), while the row signifies the authentic number of heartbeats delivered in the standard MIT-BIH arrhythmia database. The classification result for the introduced work is more than 99.5% with 16 altered types of heart disease classes.

The performance of the proposed Heartbeats Classification Model (HCM) is validated with evaluation parameters for example accuracy, error rate, sensitivity and specificity with classification time with ten samples of Electrocardiography (ECG) signals to check efficiency, these are specified in Table 3 and graphs are specified in the ensuing section.

Figure 11 signifies the contrast of proposed work with previous work [1] and in Heartbeats Classification Model (HCM); the sensitivity is the rate of acceptably classified features among the total Fig. of testing feature sets. From Fig., it is clear that the rate of the truly classified feature during the testing of an Electrocardiography (ECG) [23] signal beats is better than the work proposed by Sandeep Raj and Kailash Chandra Ray [1]. So we can say that the rate of the sensitivity of proposed Heartbeats Classification Model (HCM) is directly proportional to the efficiency of the system. If the sensitivity rate of the system is high, then their efficiency will be better and this achievement is done via using the concept of optimized Convolutional Neural Network (CNN) with basic pre-processing steps. The formula of sensitivity rate is described from the definition is written follows:

$$\text{Sensitivity}, S_e = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

Specificityrate refers to the rate of correctly classified R-peak and R-R intervals feature in all detected features. Based on these definitions, the specificity rateof proposed Heartbeats Classification Model (HCM) can be defined as:

$$\text{Specificity}, S_e = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{6}$$

So we can say that the rate of specificity of proposed Heartbeats Classification Model (HCM) is directly proportional to the efficiency of the designed system. Figure 12

Table 2 Confusion matrix of proposed heartbeats classification model (HCM)

		Correctly Classified Heartbeats = 86005Accuracy = 99.58 % Misclassified Beats = 108Error Rate = 0.42 %																
		Actual Beats																
	Class	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**Total**
Predicted Heartbeats	**1**	63181	41	0	286	139	0	27	0	71	0	15	7	0	0	0	0	63767
	2	21	5216	0	0	15	0	0	0	0	0	0	0	0	0	0	0	5253
	3	71	0	4628	11	6	0	0	0	0	0	0	0	0	0	0	0	4716
	4	18	7	0	1609	4	0	0	13	4	0	0	0	0	0	0	0	1655
	5	21	13	0	0	4576	0	0	5	11	0	0	0	0	0	0	0	4634
	6	0	0	27	0	0	4501	0	0	0	0	0	28	0	0	0	0	4566
	7	8	0	0	0	6	0	61	0	0	0	0	0	0	0	0	0	75
	8	0	0	0	0	37	0	0	199	0	0	0	0	0	0	0	0	236
	9	13	0	0	0	11	0	0	0	385	0	0	0	0	0	0	0	401
	10	9	0	0	2	0	0	0	0	0	85	0	0	0	0	0	0	96
	11	7	0	0	3	0	0	0	0	0	0	102	0	0	2	0	0	114
	12	11	3	0	0	0	6	0	0	0	0	0	481	0	0	0	0	491
	13	4	0	0	0	0	0	0	0	0	0	0	0	49	0	0	0	53
	14	2	0	0	0	0	0	0	0	0	0	0	0	0	39	0	0	41
	15	5	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	8
	16	3	0	0	0	2	0	0	0	0	0	0	4	0	0	0	7	16
	Total	**63374**	**5281**	**4655**	**1911**	**4796**	**4507**	**88**	**217**	**471**	**85**	**117**	**520**	**49**	**41**	**3**	**7**	**86113**

Table 3 Performance parameters of proposed work

ECG Signal No	Sensitivity		Specificity		Time (S)		Error (%)		Accuracy (%)	
	Existing	Proposed	Existing	Proposed	Existing	Proposed	Existing	Proposed	Existing	Proposed
1	0.934	0.985	0.932	0.989	3.92	1.33	1.94	0.07	98.06	99.93
2	0.934	0.974	0.843	0.882	4.42	1.54	0.88	0.58	99.12	99.42
3	0.945	0.996	0.913	0.938	6.44	1.75	1.17	0.17	98.83	99.83
4	0.885	0.957	0.935	0.984	4.23	1.06	0.53	0.53	99.47	99.47
5	0.956	0.946	0.896	0.963	3.34	1.64	0.87	0.56	99.13	99.44
6	0.835	0.927	0.917	0.964	4.34	1.33	1.23	0.55	98.77	99.45
7	0.928	0.929	0.954	0.992	2.55	1.64	2.55	0.58	97.45	99.42
8	0.947	0.953	0.846	0.883	3.66	1.68	0.57	0.57	99.43	99.43
9	0.988	0.992	0.864	0.837	3.88	1.28	1.89	0.43	98.11	99.57
10	0.973	0.979	0.928	0.972	3.95	1.68	0.26	0.22	99.74	99.78
Avg	0.933	0.964	0.903	0.941	4.073	1.493	1.189	0.426	98.82	99.58

represents the specificity of the proposed model in seems to better achievement.

Figure 13 signifies the comparison of proposed work with previous work [1] based on the execution time of the model. Form the analysis, we observed that the execution time of the proposed model is very low and it is improved by using the concept of Grasshopper optimization Algorithm (GOA) based Convolutional Neural Network (CNN) architecture.

A comparison of an error rate of introduced work with previous work [1] is presented in Fig. 14. The error rate is

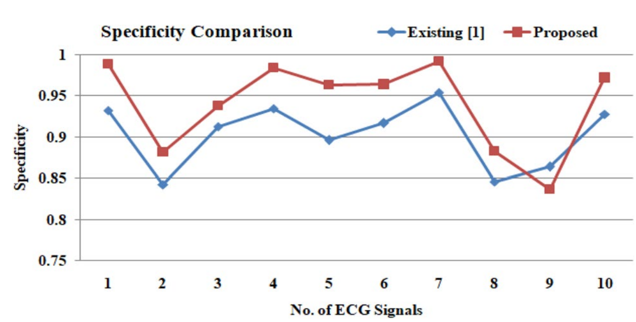

Fig. 12 Comparison of specificity

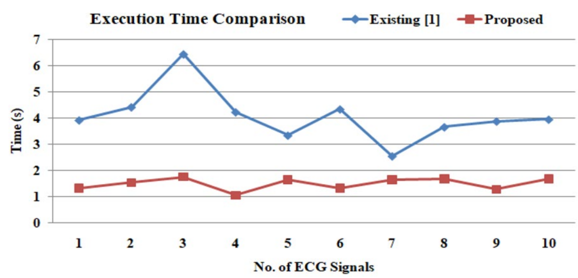

Fig. 13 Comparison of execution time

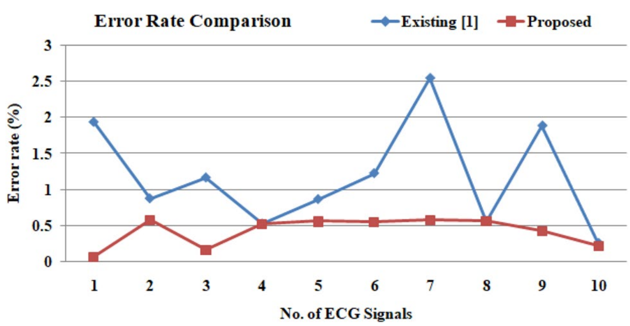

Fig. 14 Comparison of error rate

the rate of wrong classified signal concerning the total number of Electrocardiography(ECG) test signal and the formula of error rate is given as:

$$\text{Error Rate}\ ,\ E_r = \frac{\text{Total No.of worng classification}}{\text{Total No.of ECG Signal for testing}} \tag{7}$$

Figure 15 represents the comparison of proposed work with existing work [1] based on the achieved classification accuracy of Heartbeats Classification Model (HCM). The accuracy of the system represents the accurately classified ECG signal during the testing of Heartbeats Classification Model (HCM) which based on the optimized Convolutional Neural Network (CNN). Used formula to calculate the accuracy of designed Heartbeats Classification Model (HCM) is written as:

$$\text{Accuracy},\ \text{Acc} = \frac{\text{Total No.of truly classification}}{\text{Total No.of ECG Signal for testing}} \tag{8}$$

Based on the experimental results of proposed Heartbeats Classification Model (HCM), we concluded that the classification speed and accuracy are better than existing works. The HCM traing and testing accuracy is shown in the Fig. 16.

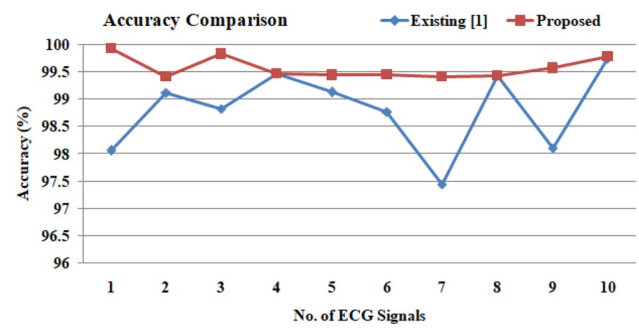

Fig. 15 Comparison of accuracy

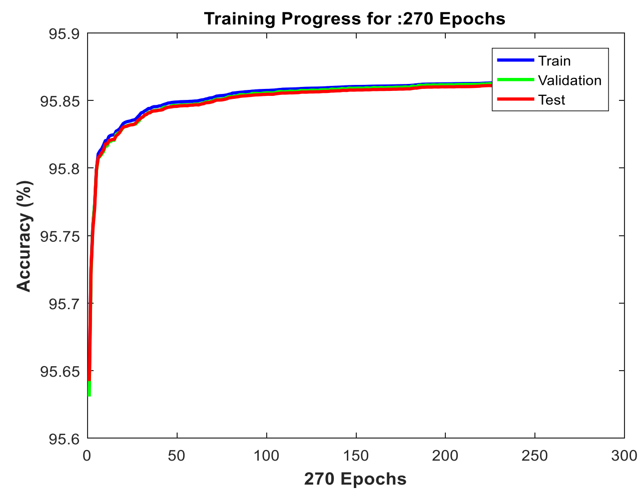

Fig. 16 CNN accuracy for HCM

In the above figure, you can clrealy see the CHM training, testing and validation accuracy for CNN.

7 Conclusion and future work

In this paper, an intellectual heartbeats classification model for diagnosis of heart disease from Electrocardiography (ECG) signal using the Hybridization of Convolutional Neural Network (CNN) with Grasshopper Optimization Algorithm (GOA) is proposed. This research is designed to solve the tasks faced by researchers in the field of disease classification using Electrocardiography (ECG) heartbeats signal. In this paper, the assortment of apposite R-peak and their R-R intervals are designed with basic pre-processing steps such as smoothing, filtering using Discrete Wavelet Transform (DWT) decomposition, etc. Grasshopper Optimization Algorithm (GOA) based feature selection approach is designed with a novel fitness function thataids to attain better classification accuracy. The proposed Heartbeats Classification Model (HCM) yields an enhanced classification accuracy of 99.58% on the standard MIT-BIH arrhythmia database which is available on the Physio Net repository. For the case of extended inception optimized Convolutional Neural Network (CNN) based Heartbeats Classification Model (HCM) used in our research, the misclassification error rate of the system is reduced up to 64% for each arrhythmia class with 63.34% faster. In future work, the Hybridization of the backpropagation concept with Convolutional Neural Network (CNN) is used as a classifier to train disease classification systems using Electrocardiography (ECG) heartbeats signals which may help to reduce the detection time of the system and can be used in the real-time scenario.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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