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Identifying arrhythmias based on ECG classification using Enhanced-PSO method

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***Abstract*---**Electrical activity generated through the Electro-Cardio-Gram (ECG) was of vast quantities of data that are produced from the individual. The study of these data enables us through the classification of cardiovascular anomalies, to diagnose disease symptoms and disorders. The classification models are extremely dynamic and representative of the usage of computing tools in the unbalanced data environments is critical, where classes are not organized equally. Besides, the efficiency of classifying the ECG it was centered on evaluating the parameter and procedures for generating a very detailed, responsive, and reliable model. Only a few optimization parameters are considered in the existing model Convolution Neural Network (CNN). Instead of an analytical tuning of data level parameters, it chooses an algorithm level which leads to poor accuracy in the unbalanced data. Therefore, the machine needs careful attention, including metrics of accuracy and precision rate. This research work proposes a metaheuristic method Enhanced Particle Swarm Optimization (EPSO) for estimating parameters for unbalanced data arrhythmias classification. To define the arrhythmia form, here it chooses an unbalanced subset from the database. It should be processed with feature extraction and feature selection approach to combine the under sampling to solve the unbalanced data issue before classification. To estimate the results for the dataset from MIT-BIH it was experimented with by the CNN and the EPSO methods focused upon different parameters such as Accuracy, F1-score, etc. The final findings of the EPSO were good than the existing CNN in which the accuracy is higher even though unbalanced data were present.

***Keywords*---**ECG, cardiovascular anomalies, convolution neural network, unbalanced data, enhanced particle swarm optimization

1. INTRODUCTION

A "Cardio Vascular Diseases" (CVD) seem to be the leading factor of mortality worldwide based on the current "World Health Organization" (WHO) report. CVD causes more deaths in million around 17.9 human beings worldwide accounting for 31% of all fatalities. Coronary arteries account for 4 of every 5 CVD fatalities, with 1/3 of such fatalities occurring before the age of 65 [1].

By detecting volts using placing electrodes to the individual's heart, forearms, and thighs, the ECG could capture the individual's cardiac electrical impulse activity across time [2]. As illustrated in Figure 1, ECGs seem to be a rapid, comfortable, and harmless approach to assess the overall heart beat, pulse, and symptoms of any possible cardiac illness.

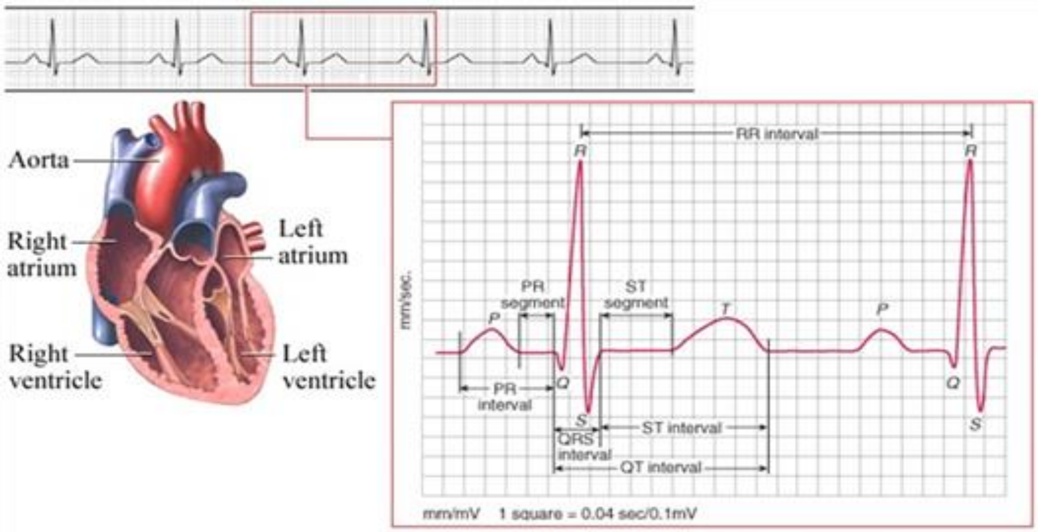

Figure 1: Recording of the ECG

(i) ECG Leads:

a. 12-Leads

This is conventional ECG leads offer horizontal and frontal observations of the cardiac, and also representations of the left ventricle's surfaces across 12 distinct viewpoints. For heart illness or soreness, electricity assaults, electrolytes abnormalities, pharmaceutical abuses, vascular disease, strokes, hypotension, and fragile individuals, these conventional ECG leads were employed mostly for arrhythmia's monitoring system. This has been often utilized in hospitals and clinics to diagnose cardiac problems [3].

b. 3-Leads

The above ECG leads are impracticable while the individual would have to be observed constantly since the individual must be linked to 10 leads. Since this normal 12-lead, ECG seems to be inconvenient for continual ECG monitoring, thus 3-leads ECG was often employed as compact ECG equipment enabling a 24-

hour capturing. Frank's model is a three-lead device that might be used in the hospital. Furthermore, extensive study has been undertaken to demonstrate that a 3-lead ECG could be used to establish a reliable assessment.

c. Compact Gadgets:

As a result of the advancement of modern wearable devices, lengthy ECG recording continuously monitors the individual's cardiac state throughout every moment and even in whatever environment is almost feasible. Compact ECG monitoring gadgets [4, 5, 6, 7] are redefining heart diagnoses through tracking an individual heart's activity 24*7 and delivering this data to a cloud platform where it may be maintained and analyzed distantly.

(ii) ECG Signals:

a. Normal Signals of the ECG:

To spot abnormalities in ECG readings, it's necessary to first understand what a normal rhythm appears as. As depicted in Figure 2, a normal heart beat has been the consequence of electrical pulses which originate from the node Sino Atrial (SA), travels throughout the cardiac muscle, and from there to the individual's heart.

Figure 2: Normal Rhythm

A normal-rhythm is formed up of the elements listed below in order. Atrial-Depolarization generates a ‘P’ wave, Ventricular-Depolarization generates a “QRS-complex”, and Ventricular-Repolarization generates a ‘T’ and ‘U’ waves. The ‘P’ and ‘T’ waves and “QRS-complex” together in a regular ECG pattern must remain consistent throughout the period all at frequencies of 60-100 bpm “beats per minute”.

Paced-Rhythm (PR) intervals could perhaps be between 0.12–0.2 seconds, and “QT” intervals need to be shorter over 50% of both the appropriate “RR” interval among a regular ECG pattern. In addition, which is illustrated in Figure 3, the difference between the minimum “PP” and “RR” intervals and also the maximum “PP” and “RR” intervals together in a regular ECG pattern shall significantly fewer than 0.04 seconds.

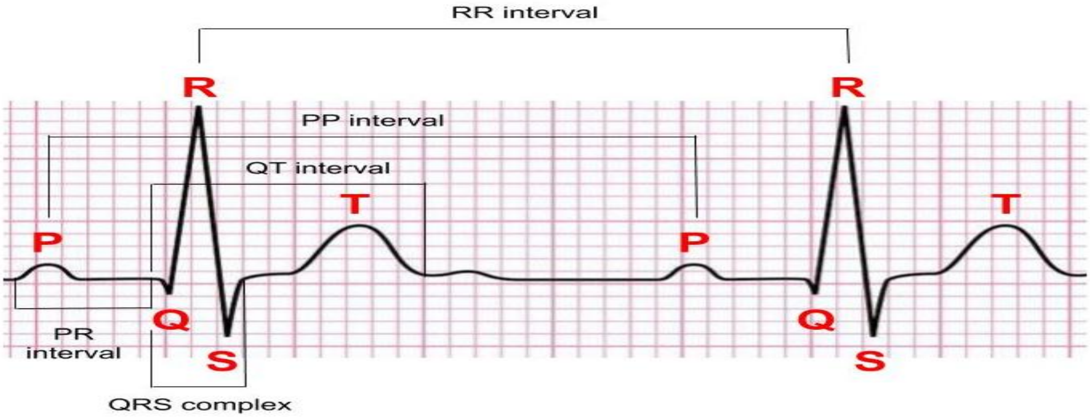

Figure 3: Notations of the Normal ECG

b. Abnormality Signals of the ECG:

Abnormalities involving ECG readings might well be grouped into 3 categories such as uneven heart rhythm, uneven heart beat, and anomalous beat.

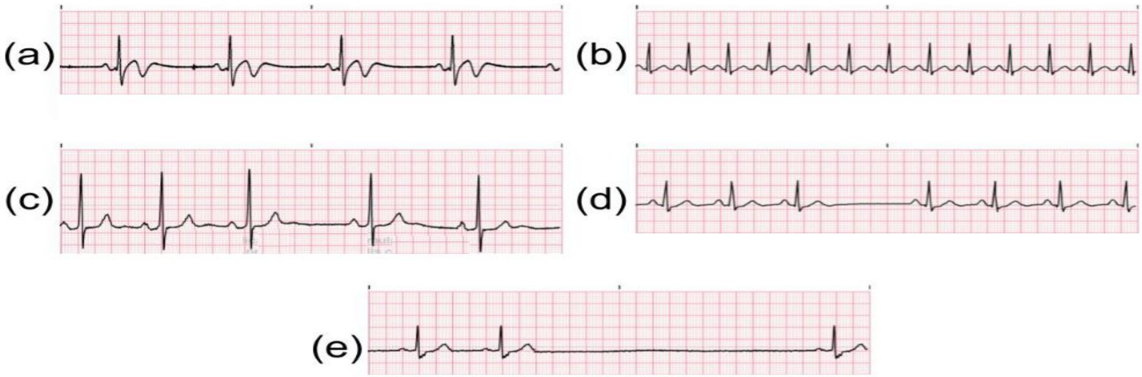

Figure 4: Abnormal Rhythms

The “PP” and “RR” intervals upon this ECG might be used to calculate the heart rate. A lengthy “PP” and “RR” intervals show the lowest heart rate, whereas a short period implies the highest heart rate. When the heart beats begin at the “SA” node yet somehow the “PP” and “RR” intervals are prolonged than ‘1’ second, this might be “Sinus-Bradycardia” (Figure 4a), which also means the heart is beating too slowly. “Sinus-Tachycardia” might have been detected whenever the “PP” and “RR” intervals were much less than 0.6 seconds (Figure 4b). Furthermore, when the differences between the “PP” and “RR” intervals are excessively big, “Sinus-Arrhythmia”, “Sinus-Block”, and “Sinus-Arrest” (Figure 4c–e) might have been present. Those ECG abnormalities might be a sign of an individual's ongoing status.

(iii) Unbalanced Data:

When the proportion of findings for each class wasn’t distributed equally, unbalanced data contributes to bad classifications. This signifies either ‘1’ or ‘n’ classes (defined as majority classes) have a lot of information and ‘1’ or ‘n’ alternative classes have a short of information (defined as minority classes). Unbalanced data is a concern in several datasets utilized for cardiac arrhythmia categorization. The characteristics of arrhythmias, those have been heart irregularities that do not arise on such a routine basis, contribute to the unbalanced data. It happens whenever ECG data from an individual identified as experiencing arrhythmia was acquired using an instrument termed Holter, which is used to examine the individual's heart signals for so many periods. The arrhythmia would most certainly establish for very several seconds throughout this period, and also the signaling would be conveyed regularly for the remaining period.

The motivation for this research stems from the fact that such enormous data sets are not particularly applicable to the healthcare world, which often lacks the resources or time to review lengthy ECG readings (three to four weeks) to discover any serious cardiac abnormalities. Fully automated and trustworthy cardiac abnormality identification techniques should be designed to facilitate clinicians in dealing with that kind of enormous database in favor enough for a system to operate.

The problem statement of this research is to evaluate how imbalanced datasets influence the effectiveness of classification metrics including such accuracy and precision, and also the consequences of this situation. A few of the earlier cited papers, for instance, exhibit lower levels for such measures [8, 9]. Due to various arrhythmias diagnosis and analysis, when the individual wasn’t properly assessed she or he might not get treated, or perhaps the individual may be mistreated when the incorrect medications are prescribed. Metrics enhancements are required to prevent False-Positives and False-Negatives.

The objective of this article is to enhance the classification performance in the situation of unbalanced datasets, which might assist in the development of services to support clinicians in the diagnosis of arrhythmias but also individual medical services.

This research contributed to the handling of cardiac signs which one final second as opposed to regular cardiac signs which lasting hours or even days. As a result, while synthesizing ECG databases, they are not automatically balanced. To put it another way, a balanced database would never be produced. Once the signals have been recorded and the databases have been formed, the imbalance issue may be largely minimized by employing one of 2 methods: over sampling or under sampling; each has its own set of benefits and drawbacks. In this research, it has been selected under sampling in this circumstance since over sampling demands the validation of synthetic-information. Before proceeding to EPSO classification, we undertake the extraction of features and feature selection. Eventually, the evaluation measures for CNN and EPSO classification methods are presented.

The remainder of the article is divided into the following sections: Section 2 gathers relevant works connected to the research topic, Section 3 summarizes Methodologies with existing and proposed models, Section 4 examines implementation outcomes with comparison, and lastly, Section 5 summarizes the conclusion and future scope of this paper.

2. RELATED WORKS

The researchers created an adaptable CNN for an individual based ECG arrhythmia categorization in [10], that combines classical extracting the features and categorization in a simple classification framework.

The researchers presented a 9-layer CNN for classifying the MIT-BIH heart beat samples into 5 distinct classes in [11]. Those who produced synthesized heart rhythm through altering the descriptive and inferential statistics of the Z-score computed from the source information to counteract the unbalance in the frequency of heart rhythm throughout the 5 (V, Q, F, S, N) classes. All other kinds' signals are augmented to compare the proportion of heart rate mostly in N class. Once the system has been trained primarily with the processed information the authors attained an accuracy rate of 94.03 percent, however, while the system was trained solely with the raw information, the accuracy rate was lowered to 89.07 percent. Throughout the trained and tested stages, the resulted heart beats were processed.

The researchers developed a CNN-LSTM combination for identifying 5 kinds of arrhythmias with varying frequency sequences using the MIT-BIH databases in [12]. A 6 pooling and convolutional layers have proceeded from an LSTM structure and 2 completely linked layers inside the framework. The time data was obtained again from feature vectors produced by the convolution layer using LSTM. The precision was found to be 98.10 percent.

The researchers suggest using DWT in combination with the 1D-HLP approach for automatic arrhythmia identification [13]. Utilizing a 1 Nearest-Neighborhood (1NN) classification, an accuracy rate of 95.0 percent was attained employing 10 seconds portions of 17 ECG categories from the MIT-BIH databases.

The system layout of MFB-CNN was modified in [14], with the completely linked layer being substituted by LSTM for describing all the nodes. Moreover, during every training case, certain nodes were disabled at randomness to improve the system's generalization. Despite this, there seems to be a gap in diverse training.

3. METHODOLOGIES

The goal of identifying changes in cardiac over ECG data is to locate abnormal heart rhythms, beats, and rates. To accomplish this, an abnormality identification model should be capable to identify abnormalities across consecutive heart rate cycles through evaluating the necessary measures. In addition, the research investigated the whole recordings for any unusual rhythmic portions, including uneven R-R intervals or extraneous beats. An abnormality identification method is made up of many modules, including denoising, heart rate segmentation, feature extraction, feature selection, and heart beat classification.

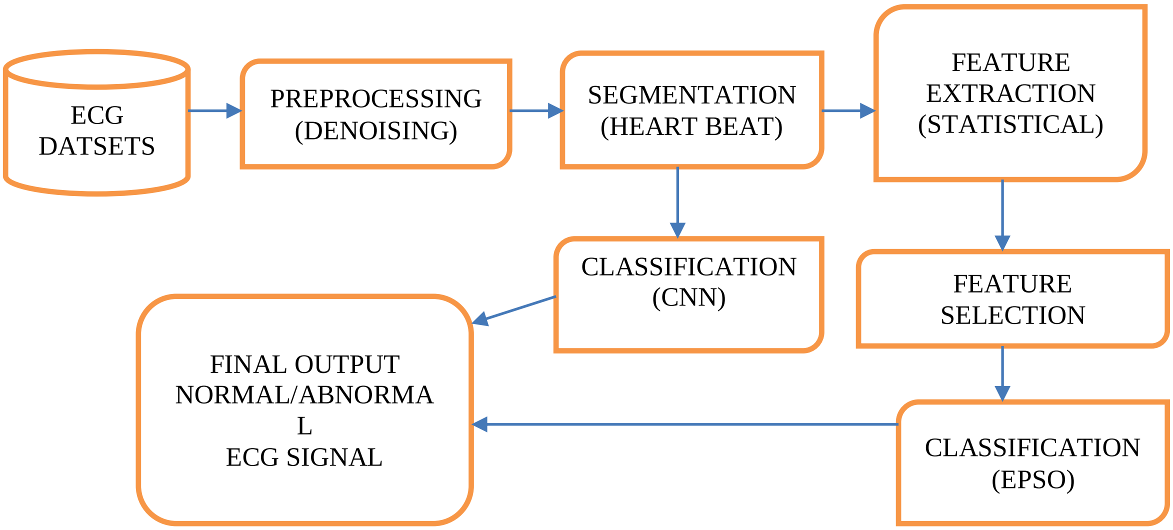

Figure 5: Proposed Heart beat Abnormality Identification Model

Figure 5 depicts the proposed Heart beat abnormality identification model. The denoising approach aims to reduce the noise by the impact of the recording equipment or the individual's motion on signal processing. Depending on a recognized pulse region, the heart rate segmentation retrieves the exact pulse. The feature extraction process picks out the most important features from the segmented area. The feature selection picks the best features to enhance the classification process Finally, the heart beat classification examines any irregular heart beat pattern on the ECG data.

3.1 Denoising

Several more disruptions which hadn't anything to deal with cardiac processes might cause ECG readings to be misinterpreted. The ECG distortions come in a multitude of shapes and sizes. These physiological distortions may be mistaken for genuine arrhythmia, resulting in incorrect diagnoses. As a result, noise reduction is required for abnormality identification in peripheral ECGs. Denoising has been used as a first phase throughout this research to reduce noise and prevent edge effects at the endpoints of signal segments. Filtering of the data is required to remove power-line interfering at 50 or 60Hz, baseline-drift or baseline-wander is about 0.5 Hz, aspiring fluctuations above 50 Hz, and higher and lower frequency noisy elements that impede signal interpretation. “P-wave”, “QRS-complex”, and “T-wave” are the three main components of ECG signals, with frequency in the range from 5 to 40 Hz.

The Discrete Wavelet Transform (DWT) filtering technique was utilized in this research since it has so far been a valuable model for examining non-stationary data like ECG. To eliminate disturbances like electromyogram-noise, power-line interference, and higher-frequencies noisy components from ECG data, here it uses this interval dependent denoising approach. To begin, it will employ the “Daubechies-6” (db6) wavelet structure to decompose with 9 levels. Furthermore, leveraging the db6 wavelet structure, the model rebuilds the decomposed signals then establishes an effective decomposition over 9 levels to the rebuilt signal, deleting the 9th level approximated subsection bands to eliminate baseline-wandering distortion. Lastly, the model denoises and smooth the ECG signal by reconstructing it with precise components ranging from 1 to 9 sub bands.

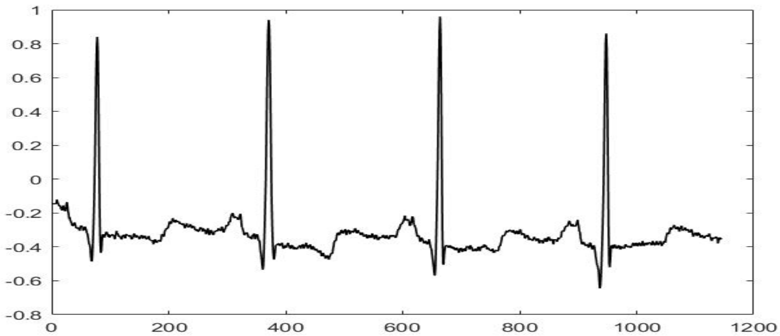

Figure 6 (A): Noisy Signals prior Filtering

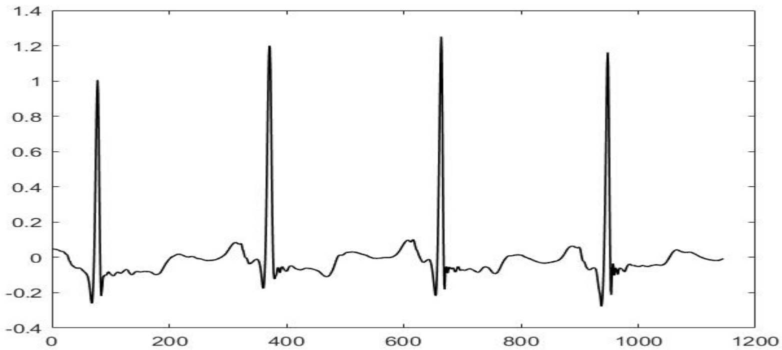

Figure 6 (B): Clean Signals post Filtering

Figure 6 (A) and (B) depict the very original signals both prior and post its filtering procedure. Figure 6.A depicts an original signal with 2 kinds of noise: power-line interfering and baseline-wandering. The signal in Figure 6.B has been wavelet filtered by eliminating power-line interfering and baseline-wandering, and it is cleaner than that of the signal illustrated in Figure 6.A.

3.2 Segmentation of Heart beats

The term "Heart Beat Segmentation" refers to the process of segmenting each heart rhythm first from the beginning of its “P-wave” to the finish of the “T-wave”. Furthermore, in other forms of irregular heart beats, the “P-wave” and “T-wave” might not have been visible, and thus the “QRS-complex” is perhaps the highest visible waveform. As a result, the position of the “QRS-complex” is frequently utilized to determine the source of a heart beat. As illustrated in Figure 7, the Pan–Tompkins method is among the foremost prominent and pioneering method that was used in this research. Because of its resilience and computationally efficiency, it is frequently employed in a multitude of scenarios. The approach reduces the noise level by using a filtering bank that includes filters based on Band-Pass, a Differentiation, filters based on Squaring, and a movable Window-Integrator to retain mainly R-wave values.

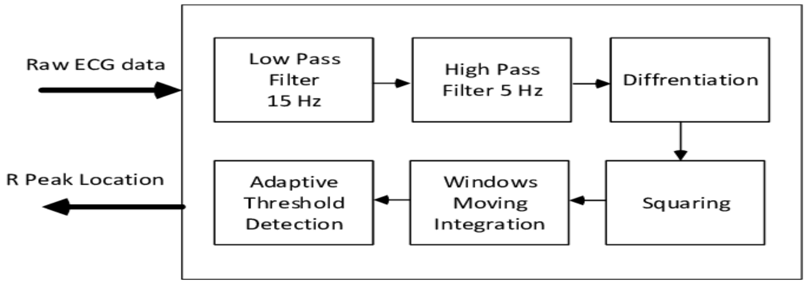

Figure 7: Architecture of Pan Tompkins Method

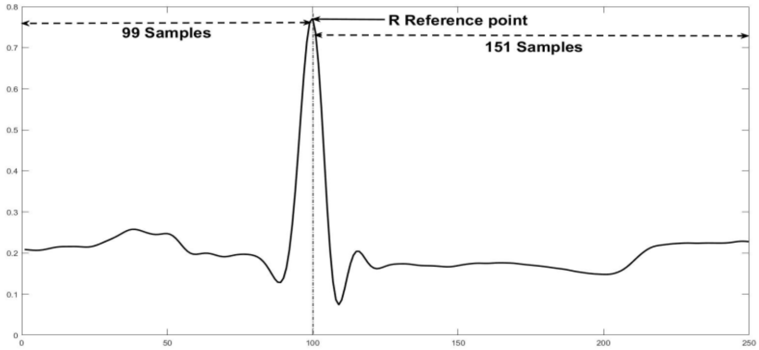

Figure 8: Segmentation of Heart Beats

A regular adult's heart beat should be about 60 bpm. That there's no set amount of sample points for every segment, however approximately 200 and 300 sample points are suggested. Here it selected 250 sample points, yielding 0.69-second segments that encompass the "P-wave", "QRS-complex", and "T-wave". Before beginning segmentation, it must first find the heart beat indication. Next, using the "QRS-complex" position as a point of reference, it chooses 99 sample points from the left end of the ECG signal and 151 sampling points from the right end as shown by Figure 8.

3.3 CNN CLASSIFICATION [Existing Model]

The emergence of Convolutional-Layers (CL) is a key component of CNNs. Through convoluting well with the source through using Convolution-Kernel (CK), the CL substitutes the generic matrices multiplying process. The CK is accomplished by utilizing sparse connections since their size is much less than the size of the input. The properties of sparse connection and parameters exchange significantly decrease the portion of parameters within CNN and also the network's computation time. A pooling-layer, also known as a sub sampling-layer, is frequently added to the CNN to further lessen the scale of calculations. The pooling-layer represents the features of a region by using the general features of the nearby region of a source region. The maximal pooling method, for example, employs the maximal values in the nearby region as the outcome, while the averaging pooling method utilizes the averaged values within the neighboring region. The frequency of units following pooling is greatly decreased since pooling integrates the response of all neighboring units. As a result, the computation productivity increases.

Numerous ECG signal processing and computation applications were already effectively accomplished using CNNs, which supports the use of CNN's but also it's associated networks for retrieve and categorize ECG signal properties. The original ECG signal being processed through two 1D-CLs in a row before being sent into the dashed box's convolution module. There have been four modules overall in the convolution module, each with three CL. The CL throughout the model had a total number of filters of 5. The initial and 2nd CLs each had 32 convolution kernels, whereas the 4 modules inside the dashed box had 64, 96, 128, and 160 convolution kernels, accordingly.

3.4 PROPOSED MODEL

It under sample the majority-classes, extracts features centered on a chosen sub segment, then merges the obtained features of classes with the majority with all instances of classes with the minority to create a unique subset. Through an algorithmic basis, these method uses for the retrieval of important content. In addition, this research used a selection of optimal features strategy to lessen the large data dimensions and increase the efficiency of the classification.

3.4.1 EXTRACTION OF FEATURES

Impact of information collection required to distinguish between arrhythmic heart rate, the feature extraction method is important for categorizing ECG data. The features belonging to statistical are obtained since they enable identifying changes amongst heart beats by analyzing the kind of dispersion and the degree of complication that ECG signals portray.

The splitting of the heart beat into sub segments is the very first stage in extracting features. It split every heart beat into sub segments containing equivalent portions of samples because every heart beat comprises 250 samples. Five statistic features have been extracted for every sub segment. Numerous split possibilities are available for sub segment partition. 5-sub segments with 50-samples (receiving 25-features), 10-sub segments with 25-samples (receiving 50-features), 25-sub segments with 10-samples (receiving 125-features), and 50-sub segments with 5-samples (receiving 250-features), to mention a few instances. It can see that the dimensions start to expand after 25-sub segments. Segments with size 5 or segments of size 10 are therefore the 2 main plausible alternatives. In terms of picking amongst those 2 possibilities, it discovered that using 10 sub segments (50 features) produces better results than using simply 5-sub segments (25-features). As a result, Figure 9 depicts the segment subdivision and also the sequence in which every feature appears. Standard-Deviation, Mean, Energy, Kurtosis, and Skewness are the statistical features retrieved for each segment. The total range of features together at end of the procedure is fifty.

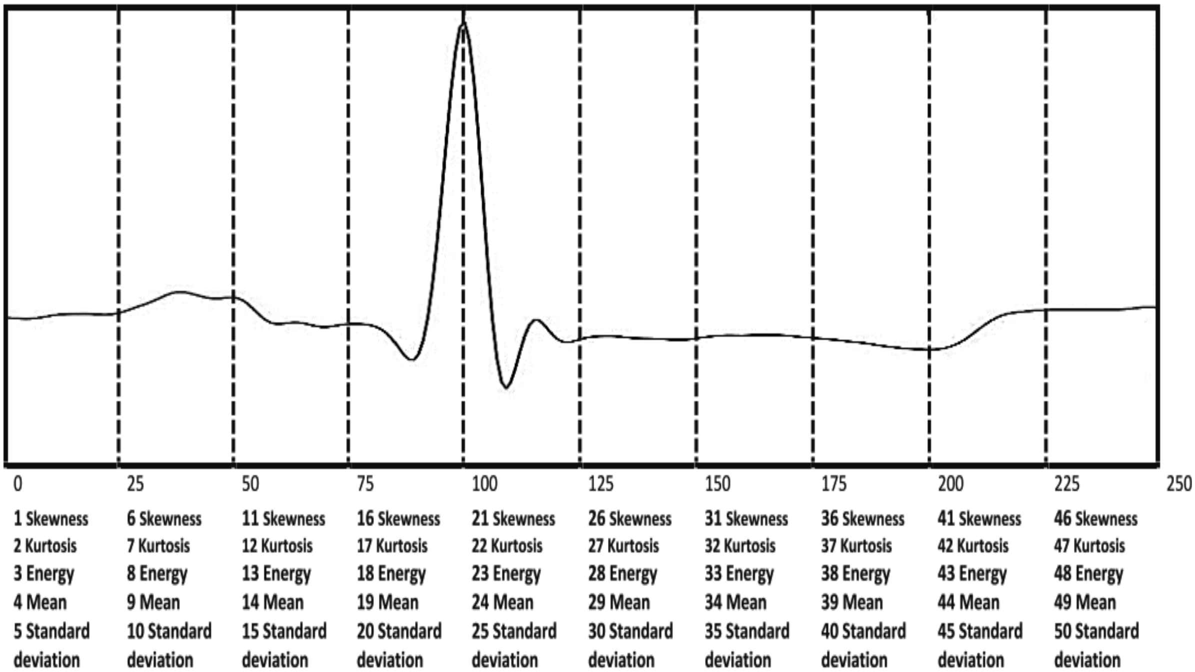

Figure 9: Extraction of Features from Segments

3.4.2 SELECTION OF FEATURES

It chooses the scale of a 2-D feature vector in the first stage, deciding on the columns and rows to create a grid for the extracted features, with each node in the grid being an element. The overall range of elements was calculated by multiplying the total of rows by the total of columns. It evaluates feature vectors with almost the equivalent range of columns and rows, ranging from 2 to 10, 2*2, 3*3, …, 10*10. This procedure is used to evaluate the classifier's effectiveness in various settings. The vector is then trained, and when it is completed, the range of classes produced usually equivalent to or less than the proportion of elements. The centroid of every class is the weighted vector corresponding with every element. As a result, every class determines the distance between its occurrences and its center. It makes it possible to identify the occurrences that are the farthest away from the center and classify those as "noisy occurrences". Lastly, every class's occurrences were listed in increasing sequence Furthermore, the under sampling is done by picking a proportion of the occurrences that are nearer to the center of each class. As '1' value indicates that the feature is picked, whereas a '0' value indicates that it is ignored.

3.4.3 EPSO Classification:
PSO approach:

The PSO seems to be a stochastic optimization technique that is widely deployed to determine the best result. This starts with the initial populations of solutions known as particles and seeks to discover the best one. This PSO technique is inspired by many animals' societal and cooperating activity throughout the search process to meet their demands. To determine the particles' future places in the search area, the method uses Personal-Experience (Pbest), Global-Experience (Gbest), and present movements.

Furthermore, 2 variables "c_1" and "c_2", and also 2 randomized integers created within [0, 1], quicken the encounters, while the present flow is amplified by an inertial variable 'w'. Every 'P' particle inside the 'S' swarm was denoted by "{X, V}", whereby "X = {x_1, x_2, x_3... x_n}" denotes the particle's location and "V = {v_1, v_2, v_3... v_n}" denotes the particle's velocity. For each iteration, the particles train from one another and upgrade their awareness of where a suitable solution is located. "Pbest" maintains a record within each particle's optimum solution and its related location, whereas "Gbest" maintains a record of the swarm's optimum location. Every particle would be influenced by its present path, internal storage (Pbest), and also the intellect of its swarm (Gbest).
As per the following equations, the particles updated its positions and velocities:

$$V_{ij}^{k+1} = w \,.\, V_{ij}^{k} + c_1 \cdot \mathrm{rand}_1\left(\mathrm{Pbest}_{ij} - X_{ij}^{k}\right) + c_2 \cdot \mathrm{rand}_2 \,. \left(\mathrm{Gbest}_{j} - X_{ij}^{k}\right)$$

Eq→1

$$X_{ij}^{k+1} = X_{ij}^{k} + V_{ij}^{k+1}$$

Eq→2

The iteration-index is 'k', the velocity is 'V', the inertia-weight is 'w', the constants for attempting to control the impact of the entity and the global solution are "c_1" and "c_2", the present position is 'X', the randomized numbers are rand_1 and rand_2, and the personal best position of every particle is "Pbest". In this equation, 'i' denotes size and 'j' denotes the dimension of the population. When compared to previous optimization methods, the PSO method is straightforward to implement since it requires a fewer set of variables to alter, as shown in (6) and (7). The PSO method was enhanced in this research to improve classification performance by optimizing the training phase.

Methodology for enhancing PSO classification:

During the classification's training stage, the particles were specified as a weighted matrix linking the vector input with the hidden-units 'W' and the hidden-units interlinked well with output-units 'V'. The overall fitness of the "*i*th" particle at the "*k*th" iteration is evaluated applying the accompanying equation within the presented technique:

$$f_i(k) = \frac{1}{N}\sum_{i=1}^{N}\left(z_i^{K} - d_i^{k}\right)^2$$

Eq→3

The set of trained samples, overall outcome, and the expected outcome of the system are denoted by 'N', "z_i^k", and "d_i^k", correspondingly.

The selection of variables (inertia weight and acceleration coefficients) in the traditional PSO method seems to have a significant impact on its function. By typically, those variables are set as fixed, and also the level of the coefficient "c_2" is designed to be greater than the level of "c_1" to ensure that the PSO method converges prematurely. The inertia weight 'w' would be a further essential variable that determines the system's capacity to do both local and global searching. That variable is kept fixed throughout iterations within the standard PSO method.

For enhancing here, it introduces modified equations for all PSO variables that assure their dropping across the iterations phase in an attempt to strengthen and increase the method's local and global scanning capability in all of its stages:

$$w^{k+1} = \left(1 - \frac{k}{M}\right) \cdot w^k$$

Eq→4

$$c_1^{k+1} = \left(1 - \frac{k}{M}\right) \cdot c_1^k$$

Eq→5

$$c_2^{k+1} = \left(1 - \frac{k}{M}\right) \cdot c_2^k$$

Eq→6

The present iteration is denoted by 'k', while the maximal length of iterations is denoted by 'M'. The "*i*th" particle's Personal-Best position ($Pbest_i$) and the swarm's Global-Best position (Gbest) would be adjusted in the *k*th iteration by utilizing the following equations:

$$\mathrm{Pbest}_i(k) = \begin{cases} P_i(k), & f_i(k) \le f_i(k-1) \\ \mathrm{Pbest}_i(k-1), & f_i(k) > f_i(k-1) \end{cases}$$

Eq→7

$$\mathrm{Gbest}(k) = \mathrm{best}\{\mathrm{Pbest}_i(k)\}, \quad i = 1:S$$

Eq→8

The steps involved in EPSO classification are given below:

a) PSO method variables are specified.
b) Particle population should be initiated.
c) Assess each particle's starting fitness.
d) Pbest and Gbest should be chosen.
e) Specify "k=1" for the number of iterations.

f) PSO variables should be updated (Equations 4, 5, 6)
g) Keep updating every particle's velocity (V^k) and location (X^k) using Equations 1 and 2.
h) Measure every particle's fitness.
i) $Pbest^k$ and $Gbest^k$ should be chosen.
j) If "k<M" is true, then "k=k+1" (Update PSO parameters)
k) Otherwise, output the weighted matrix's optimal values (W_{opt} and V_{opt}) in the classification.

As previously indicated, the classifying work is dependent on a reconfigured EPSO model training. The features utilized for classification are the inputs, and the six beat classifications analyzed are the outputs. 'R' and 'T' waves, amplitudes ("R-ampli", "T-ampli"), QRS-complex and T-wave duration ("QRS-dura", "T-dura"), "ST" and "QT" segments, and "RR" intervals such as "RR_p" and "RR_f", which have been measured by calculating the distance among both the present and the prior 'R' peak and also the distance among both the present and also the next R-peak, mostly between, are among the morphological extracted features in this research. The ratios of the "RR" intervals ($ratio_1 = RR_p/RR_f$) and the 'R' peak amplitude to the "QRS-complex" duration ($ratio_2$ = R-ampl/QRS-dur).

The PSO method ($w = 0.2$, $c_1 = c_2 = 2$) is used to explore the number of elements in the solution space. The fitness value is calculated as the difference among direct and immediate outcomes well before the training period in this stage. Initially, a population of 50 particles was evaluated. The frequencies of elements in the search space are represented by the particles ("n_H" varies from 1 to 50). For each vector input, the process is performed 100 times. The optimized range of elements in the search area seems to be equivalent to 12 for both the vector consisting of 6 morphological features [R-ampl, QRS-dur, RR_p, RR_f, $ratio_1$, $ratio_2$], and the least value of error has been recognized for the vector consisting of 6 morphological features [R-ampl, QRS-dur, RR_p, RR_f, $ratio_1$, $ratio_2$]. This was simple to determine if the input ECG signal was normal or abnormal based on these numbers.

4. RESULTS AND DISCUSSION

Arrhythmia Datasets from MIT-BIH: These resources, which were retrieved from the Physio-net website, comprise 48 1/2-hour samples of 2 channel peripheral ECG readings from 47 participants. The participants comprised 25 males and 22 females, ranging in age from 32 to 89 years of age. The males ranged 32–89 years of age, while the females have been 23–89 years of age. Every recording has a frequency of 360 Hz and an 11-bit resolution across a 10mV range. There are 14 different kinds of rhythms and 17 different kinds of heart beats in the datasets. It chooses the more common components (4 majority-classes) and the least common items (4 minority-classes) from the datasets to exhibit unbalancing activity. MATLAB 2013b has been used to simulate the system.

False-Positives (FP) and False-Negatives (FN) must always be avoided while diagnosing a patient since an inaccurate diagnostic might result in the patient suffering an impairment if the improper treatment is prescribed. In this research, FP and FN are significant. The ultimate metrics have been calculated by taking the average of all class metric scores.

It uses accuracy as a metric for the classifier model's entire performance

$$Acc = \frac{TP + TN}{(TP + TN + FP + FN)} \cdot 100$$

Eq→9

Table 1: Numerical Comparison of Accuracy

ECG-SIGNALS	CNN	EPSO
ECG-1	92.12	95.31
ECG-2	94.21	96.99
ECG-3	93.71	96.11
ECG-4	91.65	94.21
ECG-5	90.24	93.71

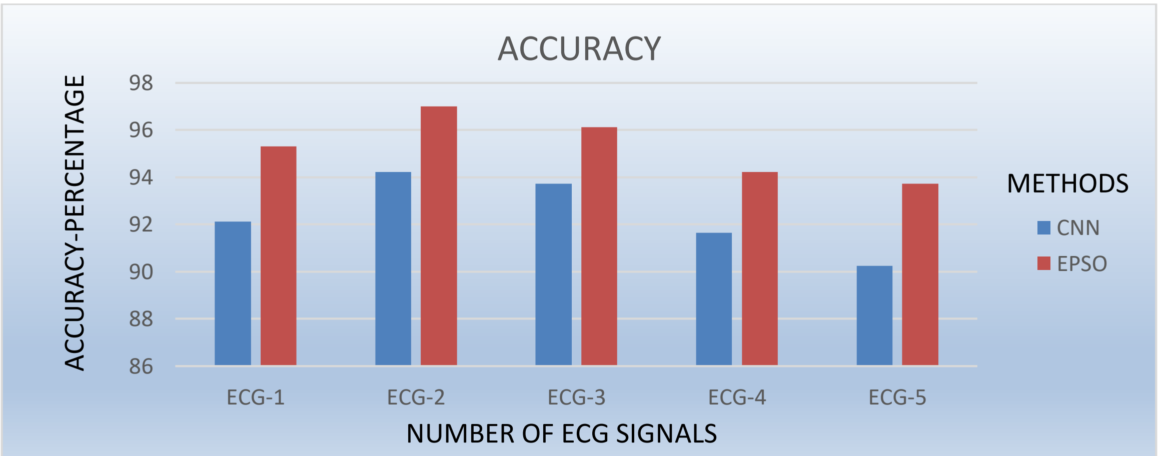

Figure 10: Graphical Comparison of Accuracy

Table 1 and Figure 10 shows the comparison of the accuracy level for both CNN and the EPSO classification. Hence it proves the accuracy is better for the EPSO as for ECG-2 is 96.99 when compared with CNN as for ECG-2 is 94.21. This proves the role of feature extraction and selection plays a significant effect in classification performance.

Sensitivity is often a measure that is connected to the FN rate.

$$Sen = \frac{TP}{(TP + FN)} \cdot 100$$

Eq→10

Table 2: Numerical Comparison of Sensitivity

ECG-SIGNALS	CNN	EPSO
ECG-1	92.02	95.22
ECG-2	94.11	96.87
ECG-3	93.59	96.02
ECG-4	91.56	94.11
ECG-5	90.13	93.62

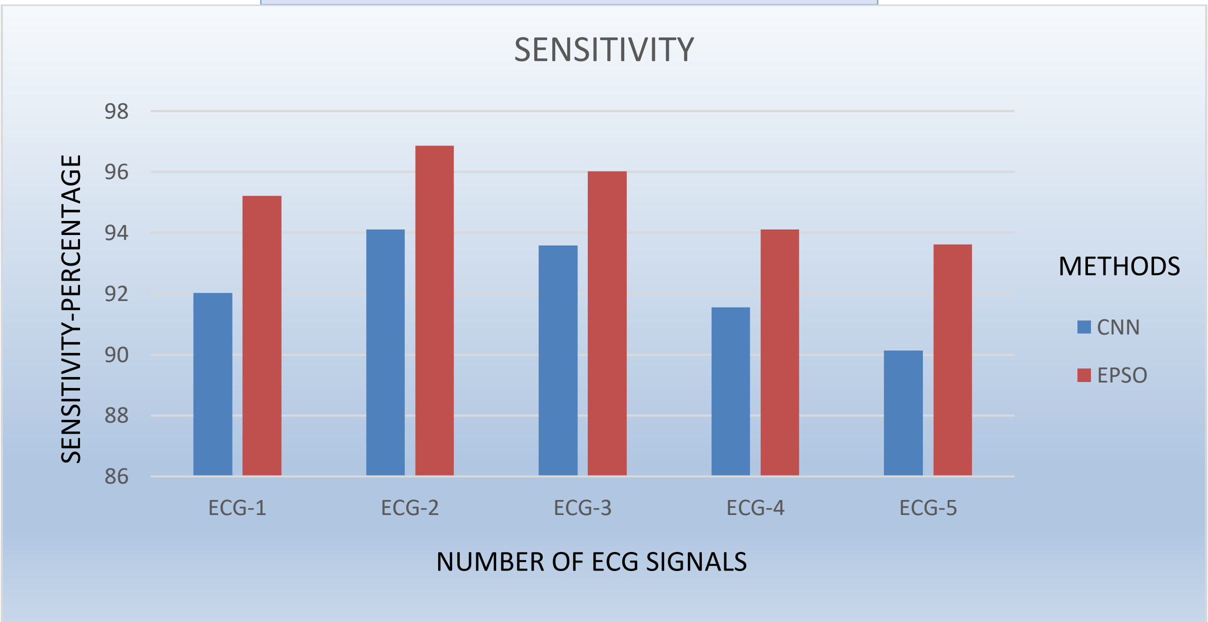

Figure 11: Graphical Comparison of Sensitivity

Table 2 and Figure 11 shows the comparison of the Sensitivity level for both CNN and the EPSO classification. Hence it proves the sensitivity is better for the EPSO as for ECG-2 is 96.87 when compared with CNN as for ECG-2 is 94.11.
Precision is often a metric that is connected to the FP rate.

$$Pre = \frac{TP}{(TP + FP)} \cdot 100$$

Eq→11

Table 3: Numerical Comparison of Precision

ECG-SIGNALS	CNN	EPSO
ECG-1	91.92	95.12
ECG-2	94.01	96.77

ECG-3	**93.49**	**95.92**
ECG-4	**91.46**	**94.01**
ECG-5	**90.03**	**93.52**

Table 3 and Figure 12 shows the comparison of the Precision level for both CNN and the EPSO classification. Hence it proves the precision is better for the EPSO as for ECG-2 is 96.77 when compared with CNN as for ECG-2 is 94.01.

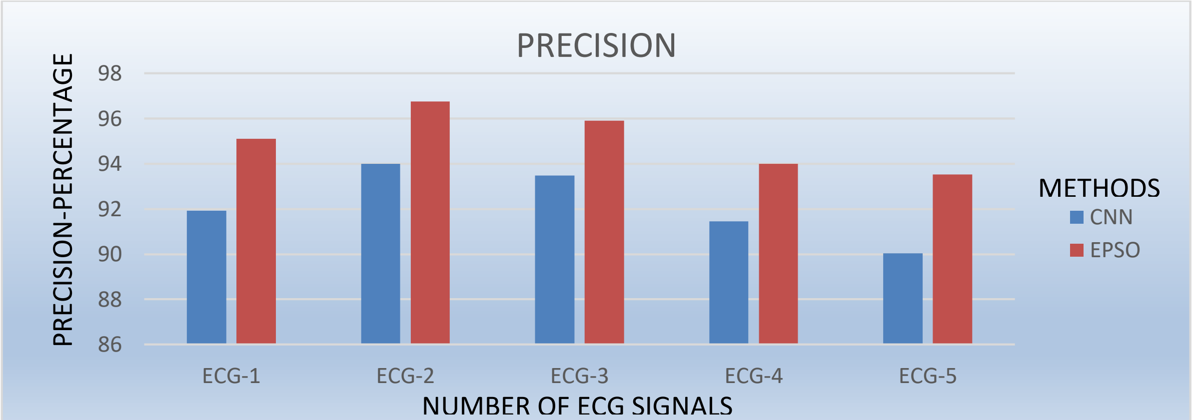

Figure 12: Graphical Comparison of Precision

While there exist unbalancing class issues, the F1-Score is computed as the harmonic mean of sensitivity and precision, considering these measures into the evaluation to measure the efficiency of the classification algorithm.

$$F1Score = 2 \cdot \frac{precision \cdot sensitivity}{precision + sensitivity} \cdot 100$$

Eq→12

Table 4: Numerical Comparison of F1-Score

ECG-SIGNALS	CNN	EPSO
ECG-1	**91.96**	**95.18**
ECG-2	**94.06**	**96.82**
ECG-3	**93.53**	**95.97**
ECG-4	**92.52**	**94.06**
ECG-5	**90.07**	**93.57**

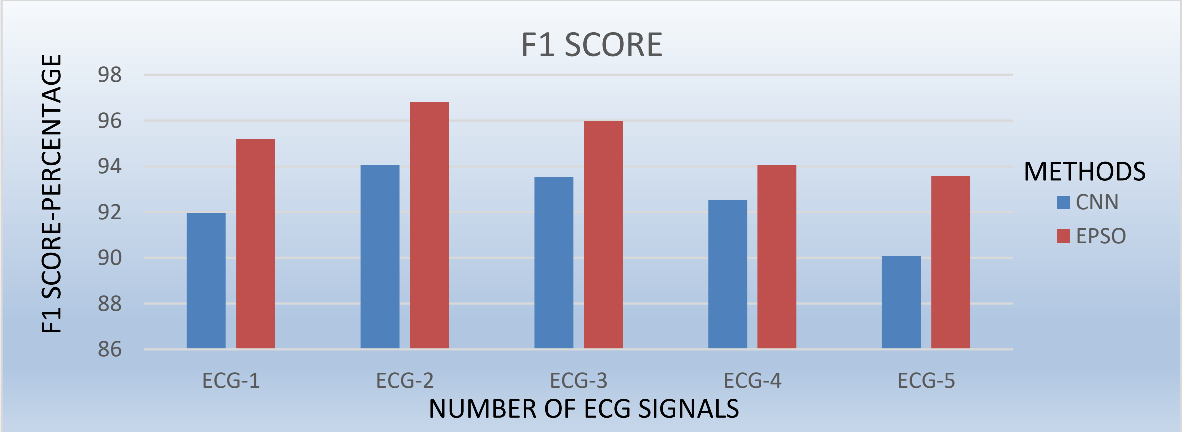

Figure 13: Graphical Comparison of F1-Score

Table 4 and Figure 13 shows the comparison of the F1-Score level for both CNN and the EPSO classification. Hence it proves the F1-Score is better for the EPSO as for ECG-2 is 96.82 when compared with CNN as for ECG-2 is 94.06.

5. CONCLUSION

The optimizing variables of the classification perform a significant part in ECG classifications when dealing with unbalanced data since performance is dependent on them. As a result, it provides a meta-heuristic EPSO optimizing strategy that combines data-level under sampling with an algorithmic level. To identify arrhythmia and a regular beat, here it used an unbalanced subset. After performing denoising and segmentation, it examined two approaches: CNN and EPSO. Once here by integrating the extraction of features and picking optimal features for EPSO classification, it gained a good accuracy. When comparing EPSO to CNN, the measures achieved were higher for EPSO. As a consequence, this finding outperforms those published in recent years. After designing a standard ECG test, this proposed model may support experienced doctors and cardiologists in correctly diagnosing an arrhythmia, improving efficiency, and reducing the frequency of medication errors. Moreover, it anticipates broad adoption of the ECG as a screening aid in distant areas whereby accessibility to cardiology wasn't available, owing to the models proposed and cost-efficient ECG equipment. Need to evaluate this methodology with more unbalanced datasets in the future, and also to reduce the computing costs associated with meta-heuristic search. This research can be extended by adding multiple kinds of arrhythmia rhythms.

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