International Journal of Scientific Research in Science and Technology
Print ISSN: 2395-6011 | Online ISSN: 2395-602X (www.ijsrst.com)
doi : https://doi.org/10.32628/IJSRST

Development of GUI in Python for Diagnosis and Analysis of ECG Signal Using Metaheuristic Algorithm

Rajas Kulkarni, Prof. Sachin Patil
Department of Computer Engineering, Zeal College of Engineering and Research, Pune, Maharashtra, India

Article Info
Volume9, Issue 3
Page Number: 836-844
Publication Issue
May-June-2022
Article History
Accepted :01May2022
Published :12 May 2022

ABSTRACT
This system effectively investigates and analyses ECG signal processing with the help of the machine learning language based tool. The study of ECG signals includes things like ECG signal generation and simulation, real-time ECG data acquisition, ECG signal filtering and processing, feature extraction, comparison of different ECG signal analysis algorithms and techniques (such as Wavelet transform), detection of any abnormalities in ECG, calculating the beat rate, and so on. To increase the performance effectiveness of evolution results, we may process and analyze ECG data in real-time and via simulation with high accuracy and ease by utilizing functions with Open CV library Python 3.6.3 machine learning a language (both built-in and user-defined).

Keywords: ECG signal data from Kaggle website, preprocessing, feature extraction, Denosing signal, Simulation by using Python Language3.6.3.

I. INTRODUCTION

Introduction An electrocardiogram (ECG) is merely a recording of the heart's electrical activity. In Fig. 1.1, sample ECG signals associated with a similar cardiac cycle are shown. The ECG is a useful non-invasive instrument for a variety of biological applications, including heart rate measurement, cardiac rhythm analysis, heart abnormality diagnosis, emotion detection, and biometric identification. The diagnosis of cardiovascular disorders is one of the most common applications of ECG analysis. Cardiovascular illnesses are the leading cause of mortality globally, according to the World Health Organization. Cardiac arrhythmias are the most frequent cardiovascular disorder, and as a result, their accurate categorization has piqued biomedical researchers' attention [4].

ECG signal exploration is one of the most effective tools for detecting arrhythmias [5]. Individual ECG beat characteristic forms, morphological traits, and spectral properties can all be investigated to yield significantly connected clinical information for automated ECG pattern detection. On the other hand, auto-mated categorization of ECG beats is a tough challenge since the morphological and temporal aspects of ECG signals change significantly for different individuals in different physical situations. The biggest issue with using ECGs to diagnose cardiac disorders is that an ECG signal can differ from person to person, and different people might have various ECG morphologies for the same ailment. Furthermore, two separate illnesses might have nearly identical features in one individual. signal from the electrocardiogram These issues exacerbate the difficulty of determining the source of heart disease. The electrical signal of each heartbeat must be evaluated to find irregularities in the heartbeat. As a result, assessing long-term ECG recordings, particularly for bedside monitoring or wearable online health care monitoring, can be a difficult and time-consuming task for a person.

The use of ECG analysis in fields other than cardiovascular disease diagnosis has exploded in recent years. Many studies have used ECG signals for emotion recognition, especially for stress level detection, in addition to a variety of other signals such as the electroencephalogram, skin temperature, blood pressure, electromyogram, heart rate variability, cortisol levels, and thermal imaging characteristics. ECG signals are recorded throughout a variety of stressful situations, such as during an oral exam, after a vacation for students, in the workplace for office workers, and while driving for drivers. These studies indicate that ECG signals may be used to distinguish the characteristics of different mental workloads and stress levels.

Furthermore, ECGs are employed in the field of biometric identification. Biometric recognition uses physiological traits like faces, fingerprints, hand shapes, DNA, and iris, as well as behavioural characteristics like voice, stride, signature, and keyboard dynamics, to identify an individual. Biometric systems give security and restricted access to restricted places. The aforementioned properties and attributes must fulfil the following criteria: universality, uniqueness, permanence, and assault resistance. ECG is increasingly being employed by academics in this field since it includes properties that are unique to an individual.

I. Feature extraction:

Extraction Because electrocardiography is an interpretation of the electrical activity of the heart, a clear portrayal of the ECG signal is essential for accurately detecting cardiac diseases. In the literature, several feature extraction algorithms have been described to reveal the unique information from ECG signals for various purposes, such as analysis and classification. These functions can be used independently or in combination with others. In this work, we categories ECG features into five categories: QRS, statistical, morphological, wavelet transform, and other.

II. P-QRS-T Complex features:

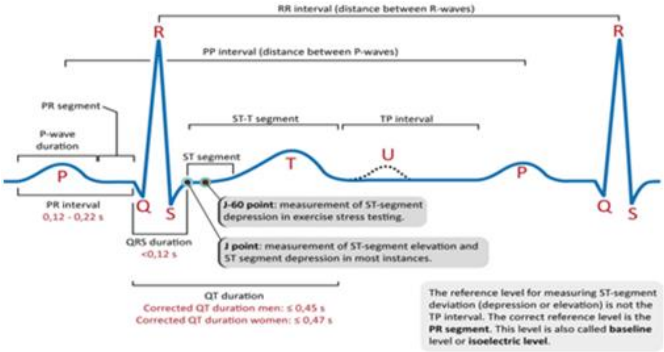

Fig 1. Complex PQRST complex features

Features For an ECG signal, the P-QRS-T complex characteristics fundamentally correspond to the positions, durations, amplitudes, and forms of certain waves or deflections within the signal [106,107]. As seen in, an ECG signal typically contains five major deflections, including P, Q, R, S, and T waves, as well as a small deflection, the U wave. The P wave is a modest low-voltage deflection away from the baseline induced by atria depolarization prior to atrial contraction as the activation (depolarization) wave-front propagates through the tricuspid valve. After the P wave, the Q wave is a downward deflection. The R wave is an upward deflection that follows the S wave, while the S wave is a downward deflection that follows the R wave. The Q, R, and S waves all point to a single occurrence. As a result, they're commonly referred to as the QRS complex.

The QRS complex features are some of the most powerful features for ECG analysis. Currents are created when the ventricles depolarize before contracting, causing the QRS-complex. Although atrial repolarization happens before ventricular depolarization, the latter waveform (the QRS-complex) has considerably larger amplitude; hence atrial repolarization isn't visible on an ECG. The T wave, which comes after the S wave, is ventricular repolarization, which prepares the heart muscle for the next ECG cycle. Finally, the U wave is a little deviation that occurs right after the T wave. The U wave travels in the same direction as the T wave most of the time.

II. LITERATURE REVIEW

The goal of this study is to identify and treat cardiac arrhythmia, which is caused by an irregular heartbeat. Examining the ECG (Electrocardiogram) data and subtracting different characteristics of the ECG signal, such as the RR interval, width of the QRS complex, P wave, R wave, and heart rate, might reveal a person's cardiac condition. The MIT-BIH arrhythmia database provided the data for the ECG signal. The Pan-Tompkins technique has been used to create a graphical user interface (GUI) for the identification of arrhythmias. A change has been made to [1-2]

The Pan-Tompkins algorithm is used to detect abnormalities. By calculating several factors connected to the heart, The MATLAB programmer was used to create this toolkit. Comprehensive research on linear, nonlinear, statistical, and time-frequency analysis of cardiac signals, as well as their parameters, has been carried out in order to determine the psychological competency of the pupils. The dominance of sympathetic nervous system (SNS) and parasympathetic nervous system (PNS) activity for balancing the autonomic nervous system (ANS) in parameters like standard deviation of NN intervals, stress index, power, and index of centralization are the key factors in determining the location of R-waves in a scalogram plot. Variables have been dissected for a final assessment. Further study of the GUI's report and the examined persons' mathematics test results supported the ascertaining approach's trustworthiness.[3]

The Pan-Tompkins algorithm is used to detect abnormalities. By calculating several factors connected to the heart, the MATLAB programmed was used to create this toolkit. Comprehensive research on linear, nonlinear, statistical, and time-frequency analysis of cardiac signals, as well as their parameters, has been carried out in order to determine the psychological competency of the pupils. The dominance of sympathetic nervous system (SNS) and parasympathetic nervous system (PNS) activity for balancing the autonomic nervous system (ANS) in parameters like standard deviation of NN intervals, stress index, power, and index of centralization are the key factors in determining the location of R-waves in a scalogram plot. Variables have been dissected for a final assessment. Further study of the GUI's report and the examined persons' mathematics test results supported the ascertaining approach's trustworthiness.[4]

The detection of physiologically significant events using both classic techniques and novel methods based on statistical physics and nonlinear dynamics, the interactive display and characterization of signals, the creation of new databases, the simulation of physiological and other signals, the quantitative evaluation and comparison of analysis methods, and the analysis of no stationary processes. Physio Net is an on-line forum for the dissemination and exchange of recorded biomedical signals and open-source software for analysing them. It provides facilities for the cooperative analysis of data and the evaluation of proposed new algorithms. In addition to providing free electronic access to Physio Bank data and Physio Toolkit software via the World Wide Web (http://www.physionet.org), Physio Net offers services and training via on-line tutorials to assist users with varying levels of expertise,[5]-[6].

We don't need to de-trend or re-sample when utilizing the Lomb-Scargle period grimmer for power spectral density estimation. As a result, when compared to the typical value of a standard measurement, all signals seem to be arrhythmic. Then, to examine the variation of heart rate in the arrhythmia database, the standard time-domain approach (statistical analysis) and the spectrum analysis of the frequency-domain method are used. The HRV analysis technique is implemented using MATLAB programming and data inputs from the MIT and BIH arrhythmia databases. [6]. Rather than giving up, the researchers considered alternative workarounds (approximation approaches) for finding a good enough answer in an acceptable amount of time; these strategies are classified as heuristics and metaheuristics. The main distinction between the two is that heuristics are used to solve problems. Heuristics are more problem-dependent than metaheuristics, which is an important distinction. In other words, heuristics might be effective in solving one problem but ineffective in solving other ones. On the other hand, metaheuristics appear to be a general algorithm framework or black box optimizer that may be used to solve practically any optimization issue.[7]

The African Vulture Optimization Algorithm (AVOA) models the foraging and navigation activities of African vultures. To assess AVOA's performance, it is first put to the test on 36 typical benchmark functions. The suggested algorithm's advantage over many existing algorithms is then demonstrated through a comparative analysis. AVOA is used to identify optimal solutions for eleven engineering design challenges to demonstrate its applicability and black box nature. According to the findings of the experiments, AVOA is the best algorithm for 30 out of 36 benchmark functions and outperforms the majority of engineering case studies. The Wilcoxon rank-sum test is performed for statistical assessment, and it shows that the AVOA algorithm is significantly superior at a 95 precent confidence range. [8]

The suggested method is compared to the most cutting-edge algorithms in the field of optimization. Additionally, five constrained engineering design issues are used as design examples, including some of the constrained optimization challenges from previous Evolutionary Computation Competitions (CEC 2020). The AOS algorithm's outcomes in dealing with constraint issues are compared to those of several conventional, enhanced, and hybrid metaheuristic algorithms published in the literature. The findings show that the suggested AOS algorithm produces excellent results when dealing with mathematical and engineering design challenges.[9]

In this paper (GEO), the Golden Eagle Optimizer, a nature-inspired swarm-based metaheuristic for tackling global optimization problems, is proposed. The cleverness of golden eagles in adjusting speed at different phases of their spiral trajectory for hunting is the source of GEO's inspiration. In the early stages of hunting, they are more likely to cruise around and look for prey, and in the later stages, they are more likely to attack. A golden eagle balances these two factors to get the best possible prey in the least amount of time. [10]

III. SYSTEM ARCHITECTURE

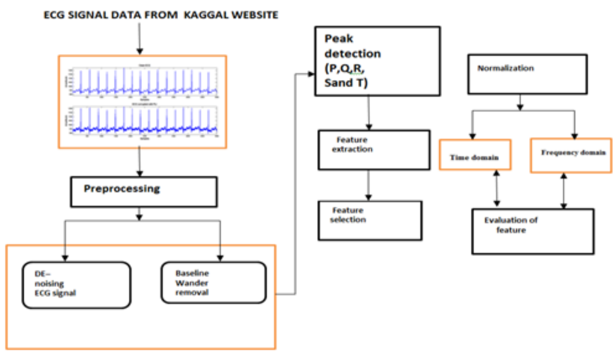

Fig 2. Anatomy of the system

The raw ECG signals are collected from the database and pre-processed to remove artefacts like baseline wander by moving average filter and the high frequency component can be removed by Savitzky-Golay least-squares polynomial filters. The features are extracted using WT(wavelet transform) to find different parameters of the ECG signal like detecting peaks (P, Q, R, S and T) and QRS interval which is helpful for diagnosing the abnormalities in ECG conditions.There are several benefits to using a simulator. ECG waveform modelling has various advantages. The first is that it saves time, and the second is that it eliminates problems. To acquire authentic ECG readings, invasive and non-invasive procedures are used. ECGs may be examined and studied using the ECG simulator. Without the use of ECG equipment, you may see normal and abnormal ECG waveforms.

1. PREPROCESSING:

There are various forms of noise in ECG signals. As a result, among other things, the pre-processing stage seeks to eliminate contamination (noise) produced by muscle noise, power line interference, motion artefact's, and baseline drift. Because the ECG signal state affects classification performance, pre-processing is required. The key processes in the pre-processing stage are depicted in Figure 3.1

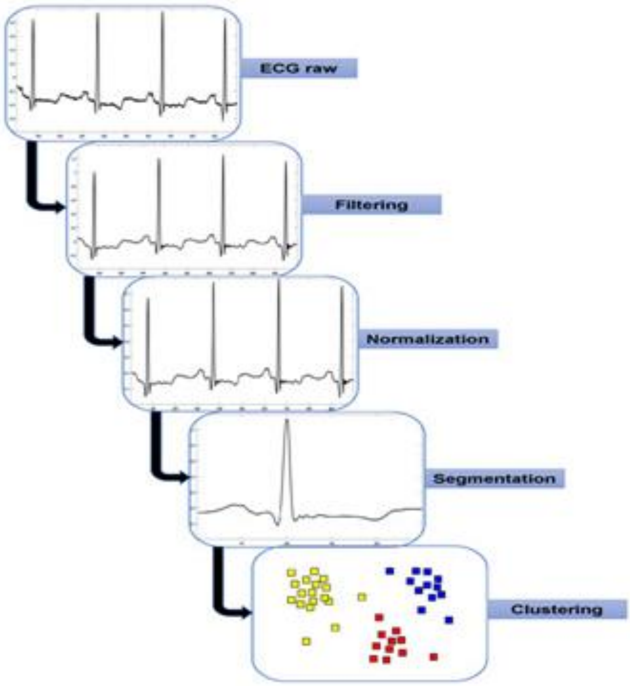

Fig 3. Stages of prprocessing

To reduce noise and avoid edge effects at the endpoints of segments of the signal, we use denoising as the initial stage of pre-processing. Filtering of the data is required to remove power line interference at 50 or 60 Hz, baseline wander or baseline drift about 0.5 Hz, electromyogram sounds above 50 Hz, and low and high-frequency noise components that interfere with signal interpretation. P wave, QRS complex, and T wave are the three main components of ECG signals, with frequencies ranging from 5 to 40 Hz. In two different scenarios, we compare two independent filtering methods. scenarios; see Section 3.1 The first filtering method is a combination of low-pass and high-pass filtering.

Wavelets are used in the second approach. The comparison's goal is to see how the filtering process affects the performance of the classifier model when different filtering methods and metaheuristics approaches are used. The low-pass and high-pass filtering methods were chosen because they have shown to be effective in reducing noise from ECG data such as muscle noise, baseline drift, power line interference, electromyography noise, and electrosurgical noise. We utilized the Fast Fourier transform approach since it has been shown to be a valuable tool for evaluating non-stationary signals like ECG; as a result, we applied a denoising procedure based on the metharustic algorithm, as did previous writers.

The identical signal is shown before and after the filtering operation in Figure 3.3. Panel A exhibits two forms of noise in the raw signal: power line interference and baseline drift. Panel B shows the signal after low-pass and high-pass filtering; the noise from the raw signal has been eliminated, but there are minor amplitude differences: in the raw signal, the Q wave is deeper than the S wave, while in the filtered signal, the converse is true. Panel C depicts the signal after it has been wavelet filtered; power line interference and baseline drift have been eliminated, and the signal is smoother than the signals in Panels A and B.

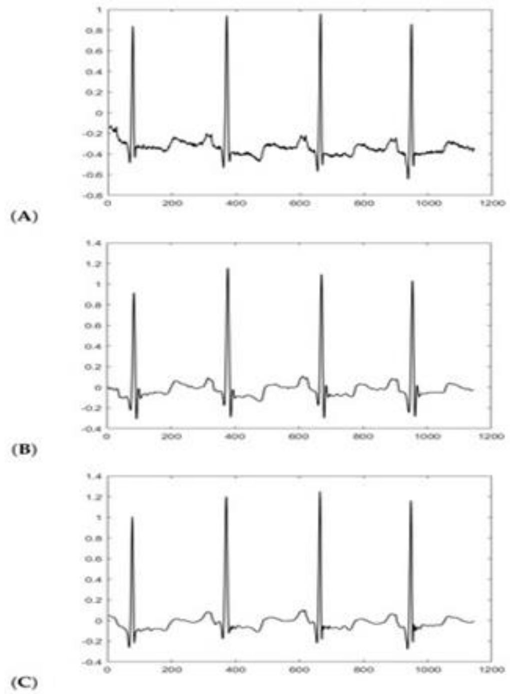

Fig 4. (A) The signal before it was filtered. (B) Signal after applying a high-pass and low-pass filtering combination. (C) After FFT ,

2. FEATURE EXTRACTION:

After elimination of noise, feature extraction is done.Detection of fiducial points (i.e. R-peaks) is the mostimportant part of ECG signal analysis. In this work, firstthe R-peaks are detected using WT, then, all other features are extracted. The methods used for detectionof features are described in the subsection ofthis section

A. R-peaks detection

In this work, detection of R-peaks is done by usingDWT along with thresholding. The following steps areused for R-peak detection;

Step 1: acquisition of EGG signals: in this study, Kaggle website database is taken as the input signal.

Step 2: elimination of different kinds of noise: elimination of noise is done using MODWT anduniversthresholding is representedby Equation (13) for n number of signal coefficients.

Step 3: peaks detection: peak detection is done usingthresholding.

Step 4: R-peak detection: R-peaks detection is per equation using

$Ri = Pi \times 2^{j}$.... Equation (1)

From kaggle website datasets have undergone thorough testing and observation. R–R intervals and heart rate are recorded once R-peaks are detected. The examination of an ECG signal does not end with the detection of heart rate. Different aberrant rhythms or arrhythmias can be seen in a normal heart rate signal. Supra-ventricular arrhythmias, atrial fibrillation, atrial flutter, paroxysmal supraventricular tachycardia, ventricular arrhythmias, ventricular tachycardia, ventricular fibrillation, and other arrhythmias are categorised. All components of the ECG signal are examined for these arrhythmias (a complete study includes amplitude and duration of ECG wave components). In order to classify ECG rhythms as normal or pathological, several parameters other than the heart rate must be extracted.

B. Q and S waves' detection

Step 1: Get an ECG signal: for Q wave detection, a 3rd level decomposed ECG signal is used (achieved by wavelet decomposition).

Step 2: create a counter: since the number of R waves is expected to be equal to the number of Q waves, set the counter to the entire number of R waves, as well as b = 1.

Step 3: Choose a time interval: Because the Q wave comes right before the R wave, the time interval is 0.2 seconds before the R wave. As a result, the time period for Q wave detection is 0.025 s, or nine samples of 3rd level decomposed signal before the relevant peak.

Step 4: locate the least amplitude point: Because Q wave is the smallest amplitude point before R wave, it may be discovered by looking for minima in a certain interval.

C. Detection of P and T peaks

P waves/peaks are detected using the following steps:

Step 1: Take an ECG signal in the first Set a counter value of i1 and a threshold value of:
Step 3: Set a time limit: Because P waves/peaks come before Q waves/peaks, the time gap between them is 0.3
Step 4: Increase i by 1
seconds. Step 5: To find the maximum amplitude of the P wave, identify the maxima of a specified part of the signal.
Step 4: Increase i by 1.
Step 5: To find the maximum amplitude of the P wave, identify the maxima of a specified part of the signal.
Step 6: Repeat for all P waves: By repeating Steps 3 to 5, i 1 counter, you may find all P waves/peaks.With the exception of step 2, the steps for identifying T waves are the same as for detecting P waves. The time interval is used in this case.

IV. METHODS AND MATERIAL

1. METAHEURISTIC APPROACH

3.fig depicts the 4.1 Figure tiers of a metaheuristic method for heartbeat class the usage of unbalanced information. The first, information acquisition, analyses the instructions the usage of information from the Kaggle internet site arrhythmia database to create an imbalance context with 4 majority instructions and 4 minority instructions. In Section 3.2, the unbalanced ratio of the brand new subset of the 8 instructions is calculated. The 2d stage, ECG sign preprocessing, includes 4 phases (see Section 4.1). To begin, we clear out the recordings to do away with noise from the alerts. Then, to lessen the version amongst affected person ECG alerts, every sign is subjected to amplitude Normalization. The filtered alerts are then divided .

2. METAHEURISTIC OPTIMIZATION:

We propose a hybrid optimization strategy based on a metaheuristic approach to handle the imbalanced class problem that combines the data and algorithmic levels to optimize the classifier's parameters. In comparable situations, we examine two metaheuristics techniques, particle swarm optimization (PSO) and differential evolution (DE), to find a combination of parameters that improves the classifier's performance.

A. Particle Swarm Optimization:

Particle swarm optimization (PSO) is a metaheuristic for optimization based on the movement patterns of birds and fish flocks. A swarm is formed by particles that change position in the standard PSO algorithm; each particle is a potential solution to the problem, and they change position according to three principles: (1) maintain inertia, (2) change the conditions according to the particle's optimal

B. Differential Evolution:

Differential evolution (DE) is a population-based stochastic method. It iteratively executes four phases to optimize real-valued functions: initialization, mutation, crossover, and selection. The following is a list of each step:
1. Initialization: A population of parameter vectors is produced at random between the lower and higher bounds in this stage.
2. Mutation: Individuals from the existing population become targets in each generation or iteration.
3. Vectors. The method picks three alternative vectors from the population at random for each target vector; subsequently, a donor vector is constructed from the weighted difference of two vectors to the third.
4. Crossover: After creating the donor vector, the recombination or crossover procedure is undertaken to increase the population's potential variety.

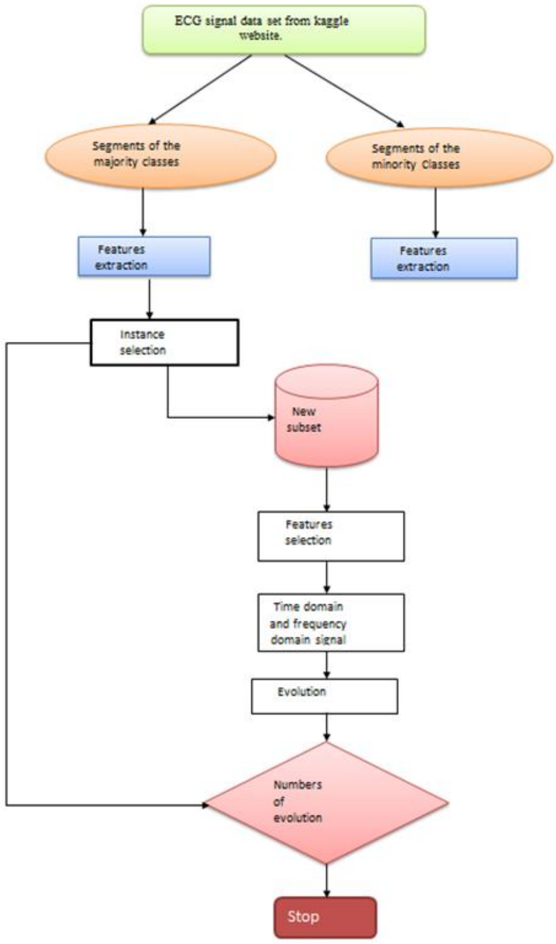

Fig 5. Metahuristic approach diagram.

Finally, the majority classes are divided into smaller groups using the clustering method. The third stage is feature extraction, in which statistical features are retrieved per heartbeat of all selected signals; see Section A hybrid technique to tackling the imbalance problem is used in the last stage, metaheuristic optimization; The metaheuristic aims to increase performance by selecting several parameters.

The classifier's output It chooses the size of SOM features maps and the number of instances (%) of each majority class cluster at the data level. The metaheuristic chooses the amount of neurons in the hidden layer of the artificial neural network, as well as the characteristics to train and test the classifier, on an algorithmic level. These parameters are represented as a vector, and the performance of each vector is evaluated using a fitness function. We go over each stage in greater depth in the above following sections.

Figure 4. depicts the four stages of a metaheuristic approach for heartbeat classification using unbalanced data. The first, data acquisition, analyses the classes using data from the Kaggle website arrhythmia database to create an imbalance context with four majority classes and four minority classes. In Section 2, the unbalanced ratio of the new subset of the eight classes is calculated. The second stage, ECG signal pre-processing, consists of four phases (see Section 2). To begin, we filter the recordings to remove noise from the signals. Then, to reduce the variation among patient ECG signals, each signal is subjected to amplitude normalization. The filtered signals are then divided into heartbeats. Finally, the majority classes are divided into smaller groups using the clustering method. The third stage is feature extraction, in which statistical features are retrieved per heartbeat of all selected signals; se. A hybrid technique to tackling the imbalance problem is used in the last stage, metaheuristic optimization; The metaheuristic aims to increase performance by selecting several parameters.

V. CONCLUSION

We have previously studied the processing of ECG signal has greatly observed by using MATLAB view, but how we design and implement our system, they are so useful and convenient that even without an ECG machine, one can monitor his or her cardiac condition by using machine learning based python to analyse abnormalities in ECG signal, which is one of the best methods to improve performance by using metharustic Approach to self-diagnosis algorithm. Even if we don't have any ECG data to replicate and analyse, the examples and approach presented here might be highly useful for experimental/lab reasons

VI. REFERENCES

[1]. Matlab based gui for ecg arrhythmia detection using pan-tompkin algorithm bhawnajindal electronics and communication engineering A.P, JMITRadur, Haryana bhawnajindal02@gmail.com SaudagarEkta Electronics and communication engineering AP, UIET Kurukshetra, Haryana ekta.tamak@gmail.com Reeta Devi2018

[2]. Advances of cardiac state-inducing prototype and design of GUI to anatomize cardiac signal for ascertaining psychological working competenceKusum Tara1,* ikusumtara@gmail.com, Md. Hasibul Islam1 ihasibul@gmail.com 1Dept. of Electrical and Electronic Engineering, Rajshahi University of Engineering & Technology, Rajshahi, Bangladesh *Corresponding author 2020

[3]. Motion Artifact Removal in Ambulatory ECG Signal for Heart Rate Variability Analysis Deepak Berwal, Vandana C. R., Sourya Dewan, Jiji C. V. and Maryam ShojaeiBaghini, Senior Member, IEEE 2019

[4]. Heart sound and ECG signal analysis and detection system based on LabVIEW Guo Ying,WangZhenzhen, KeLi,DuQiang ,Li Jinghui School of Information Science and Engineering,Shenyang University of Technology, Shenyang 110870 E-mail: wzz0903@foxmail.com 2018 IEEE

[5]. PhysioBank, PhysioToolkit, and PhysioNet Components of a New Research Resource for Complex Physiologic Signals Ary L. Goldberger, MD; Luis A.N. Amaral, PhD; Leon Glass, PhD; Jeffrey M. Hausdorff, PhD; Plamen Ch. Ivanov, PhD; Roger G. Mark, MD, PhD; Joseph E. Mietus, BS; George B. Moody, BS; Chung-Kang Peng, PhD; H. Eugene Stanley, PhD

[6]. Analysis of heart rate variability based on quantitative approach Hla Myo Tun Yangon Technological University 2018

[7]. METAHEURISTIC ALGORITHMS: A COMPREHENSIVE REVIEW Mohamed Abdel-Basset∗, Laila Abdel-Fatah∗, Arun Kumar Sangaiah† Faculty of Computers and Informatics, Zagazig University, Zagazig, Sharqiyah, Egypt †School of Computing Science and Engineering, Vellore Institute of Technology, Vellore, India 2018

[8]. African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems Benyamin Abdollahzadeh a, FarhadSoleimanianGharehchopogha,*, SeyedaliMirjalili 2021

[9]. Atomic orbital search: A novel metaheuristic algorithm Mahdi Azizi Department of Civil Engineering, University of Tabriz, Tabriz, Iran2020

[10]. Golden Eagle Optimizer: A nature-inspired metaheuristic algorithm Abdolkarim Mohammadi-Balani Mahmoud Dehghan Nayeri1,MahmoudDehghan Nayeri1,Mohammadreza Taghizadeh-Yazdi,