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REVIEW ARTICLE

Intelligent Algorithmic Approaches to ECG Signal Classification in Heart Disease Detection

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Abstract

Electrocardiography (ECG) is one of the most important non-invasive tools for detecting electrical cardiac signals. The Heart signals consider a thorough Investigation of the heart & allow for a comprehensive analysis of the heart. Electrocardiography (ECG or EKG) can employ electrodes with measurement of the electrical movement of the heart. Extracting ECG signs will be non-invasive control veer off opens the entryway on the world of inventive up and about preparing What's more perceptions dissection systems in the analysis a heart malady. With the help of today's extensive database for ECG signals an arithmetically smart system can impart and take the place of a cardiologist. Identification for Different abnormalities in the patient's heart with distinguish Different heart infections might be committed through an adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system (ANFIS) preprocessed by subtractive grouping. Six sorts of claiming heartbeats are classified: atrial premature contraction (APC), premature ventricular contractions (PVCs), a right bundle branch block (RBBB), left bundle branch block (LBBB), What's more paced thumps. The objective is to identify imperative aspects from claiming an ECG signal to figure out whether the patient's pulse is ordinary alternately unpredictable. The aim of this study is to reveal the contents of the plan signals whether natural impulses of the human heart or otherwise. We are trying through these simulation studies and knowledge of the patient's heart disease that undergo them without the need for a competent cardiologist.

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Keywords: Electrocardiography (ECG); Heart Disorders; Artificial intelligence (AI); Adaptive Network-based Fuzzy Inference System (ANFIS).

1. Introduction

ECG is a fundamental tool in the detection and classification of cardiovascular diseases (CVD). It captures the heart's electrical activity, providing critical insights into various cardiac conditions, including ischemic heart disease, myocardial infarction, arrhythmias, and cardiomyopathy. While traditional ECG interpretation relies heavily on expert analysis, the integration of intelligent algorithms has revolutionized the field, enhancing diagnostic accuracy and efficiency [1, 2].

Recent advances in machine learning (ML) and deep learning (DL) have significantly improved the classification of ECG signals. These intelligent algorithms can analyze vast amounts of data quickly and accurately, making them invaluable in clinical settings. For instance, studies have shown that deep neural networks can achieve classification accuracies exceeding 98% for detecting major cardiac abnormalities such as myocardial infarction and abnormal heart rhythms. Machine learning techniques such as support vector machines (SVM), logistic regression (LR), and adaptive boosting (AdaBoost) are commonly employed for ECG classification. These models are trained on labeled datasets, allowing them to learn patterns associated with normal and abnormal heart conditions. A notable study demonstrated that an ensemble model combining AdaBoost and LR classifiers achieved a remarkable performance with an accuracy of 94.6% on the PTB-ECG dataset2. This highlights the potential of using ensemble methods to enhance classification performance. Deep learning approaches, particularly convolutional neural networks (CNNs)[3-5], have emerged as powerful tools for ECG analysis. CNNs can automatically extract features from raw ECG signals or images, reducing the need for manual feature engineering. Research has shown that CNNs can outperform traditional methods in detecting arrhythmias, achieving accuracies greater than 99% in controlled datasets4. These models are particularly effective due to their ability to learn hierarchical representations of data [3].

Despite the promising results achieved with intelligent algorithms, several challenges remain in ECG classification. The availability of high-quality labeled datasets is crucial for robust training models. Moreover, addressing issues related to class imbalance in datasets is essential to ensure that models perform well across all classes of heart diseases.

Future research should focus on developing more interpretable models that provide insights into their decision-making processes. This is particularly important in medical applications [6-9] where understanding the rationale behind a diagnosis can enhance trust among clinicians and patients alike5. The application of intelligent algorithms in ECG chart classification represents a significant advancement in cardiovascular diagnostics. By leveraging machine learning and deep learning techniques, healthcare providers can enhance their ability to detect heart diseases accurately and efficiently. As research continues to evolve, these technologies hold the promise of transforming cardiac care, ultimately leading to improved patient outcomes and reduced healthcare costs.

2. Methods and Materials

2.1. Human Heart and ECG Relationship

The heart is a muscular organ in humans, which pumps blood through the blood vessels circulation. Blood provides the body with oxygen and nutrients and helps to get rid of metabolic waste. The human heart is composed of four chambers from the upper part of the left atrium and right atrium. The bottom of the heart is the left and right ventricles. The heart chambers are separated into four valves. One valve is located between the right atrium, the right ventricle and one valve between the left atrium and left ventricle. There is one valve at the exit of each ventricle. The valve is called between the right atrium and the right ventricle with a triangular valve. The valves between the atria and the left and right ventricles are known as ventricular atrial valves. The trigeminal valve contains three channels, which are connected to the reed tendons and three papillary muscles called the anterior, posterior and muscular muscle, after their relative positions. Between the left atrium and the left ventricle is the mitral valve. It is also known as a bivalent valve because of two protrusions, two protrusions in front and back. These protrusions are also connected to the two tendons of the ventricular wall. The papillary muscles of the valves connect to the walls of the heart through cartilage links called "chordae tendineae". These muscles are designed to prevent valves from falling when closing. The papillary muscles are relaxed during the relaxation phase of the heart cycle, and the tension on the string tendons is light. They also contract papillary muscles, as well as chambers of the heart. This results in tensile tension on the tendons, which helps to stabilize valves of the ventricular valves in place and prevent them from returning to the atrium [10, 11].

2.2. The Heart Work Aberration

Five main types of human heart disorders have been identified [12, 13].

- **Premature Ventricular Contraction (PVC):** PVC is abnormal heart beats that begin in one of the heart's two lower pumping chambers (ventricles), as shown in Figure 1. These strikes extra disable your heartbeat regularly, sometimes causing you to feel flip-flop or skipped beat in human chest [14]. Former ventricular contractions early so common - it occurs in most people at some point, and it occurs as it generates concentration in the ventricular action effort prior to the potential of the nodal procedure as described above.

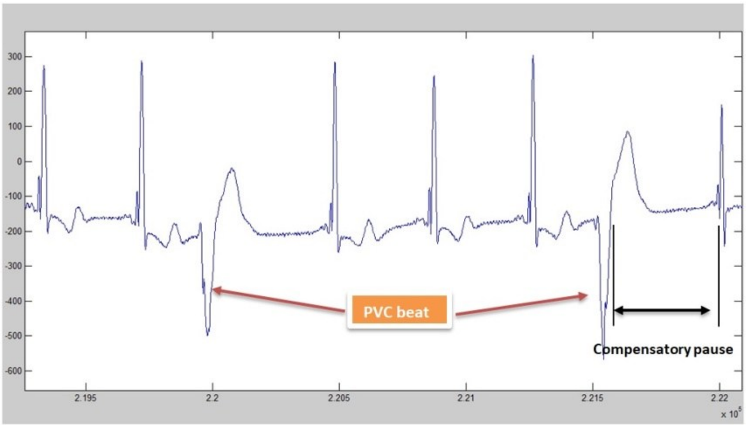

Fig. 1. The model of the ECG recorder signal shows APC beat from MIT-BIH.

- **Atrial Premature Contraction (APC): APC** is a condition caused by a cardiac dysfunction resulting in premature heart attacks by the atria, as shown in Figure 2. The sinus node usually works to regulate heartbeat during the heartbeat. APCs can occur when a part of the atrium is attracted by the sinus node and thus leads to premature heartbeat [15]. Those who receive PACs usually from older people do not need any additional attention as well as follow-up because of unclear evidence of the cause of the disorder. Most often the signal of PACs is not quite clear and can only be sensed with Holter monitoring but occasionally flares out and notes a shake in the chest upset. Holter monitoring: it is one type of ECG device, which is a portable device for heart monitoring.

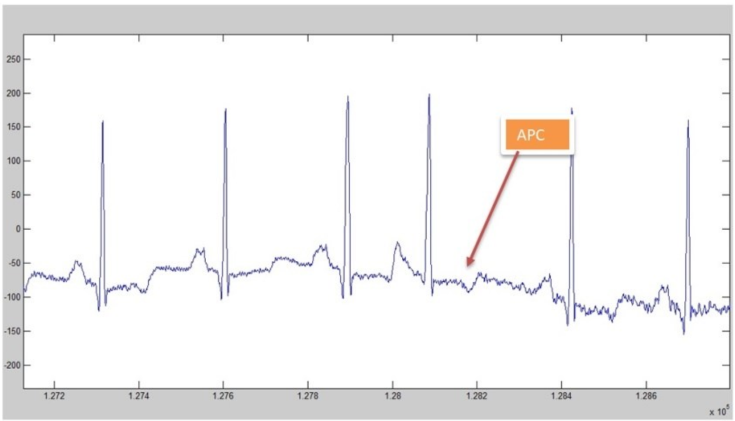

Fig. 2. The model of the ECG recorder signal shows APC beat from MIT-BIH.

- **Left Bundle Branch Block (LBBB):** LBBB is a cardiac conduction abnormality seen on the ECG [16]. In this condition, activation of the left ventricle of the heart is delayed, which causes the left ventricle to contract later than the right, as shown in Figure 3.

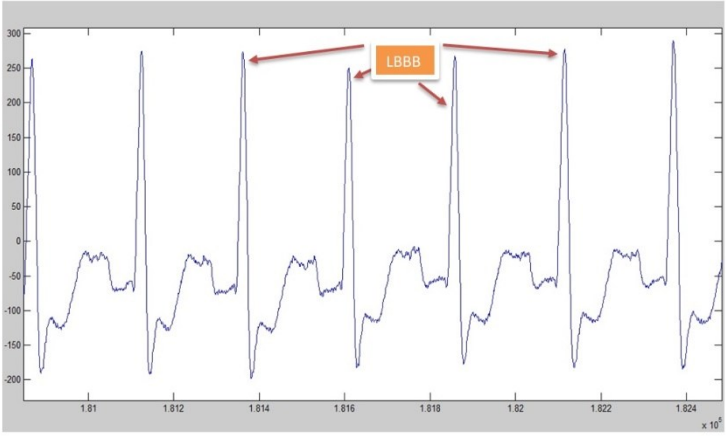

Fig. 3. The model of the ECG recorder signal shows LBBB beat from MIT-BIH.

- **Right Bundle Branch Block (RBBB):** In RBBB, activation of the right ventricle is delayed as depolarization must spread across the septum from the left ventricle, as shown in Figure 4. When the left ventricle is activated normally, this means that the early part of the QRS complex has not changed. The activation of the right ventricle allows secondary R signals (R) in the correct primary strands (V1-3) and a wide and variable S wave on the lateral sides. The delay in activation of the right ventricle also leads to secondary deformities in the retraction, with the failure of ST and the reversal of the T signal in the correct initial grades. In the isolated RBBB, the heart axis does not change, as the left ventricle is normally activated through the left bundle branch [17].

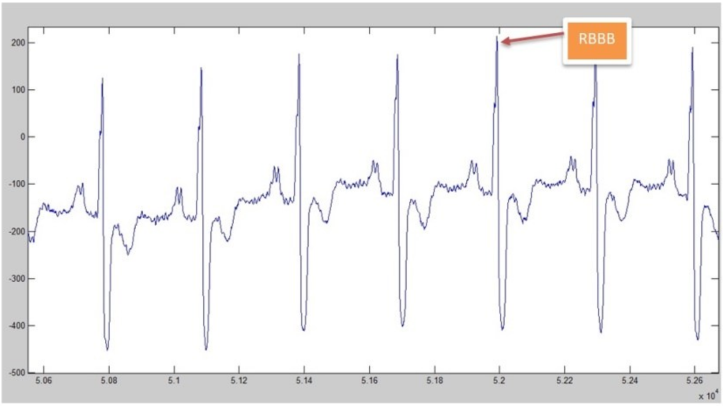

Fig. 4. The model of the ECG recorder signal shows RBBB beat from MIT-BIH.

- **Paced fusion beat:** A Paced fusion beat happens when the electrical impulses from various sources operate on the same region of the heart at the same time, as shown in Figure 5. If it works on the ventricle rooms and so-called ventricular fusion beat, while colliding currents in the atrial rooms' fusion produces a pulse flutter [13].

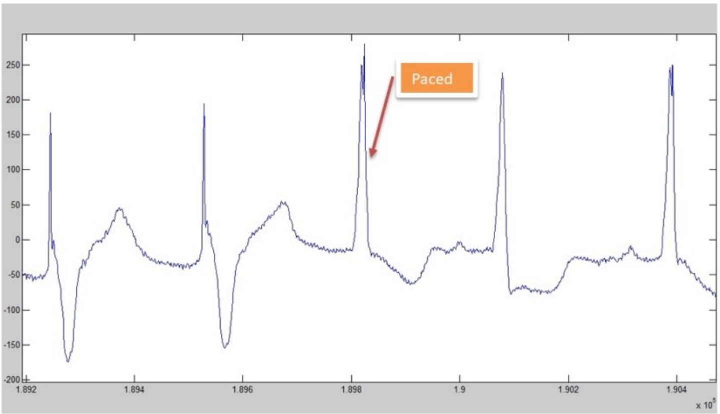

Fig. 5. The model of the ECG recorder signal shows a paced fusion beat from MIT-BIH.

2.3. Artificial intelligence (AI) and Artificial Neuro-Fuzzy Inference Systems (ANFIS) Algorithm

AI is introduced into devices. By computer science, they are ideal "smart", and the machine is a rational agent that has the flexibility to take positions and decisions programmed in advance increase the chances of success in reaching the goal. The science of artificial intelligence is embodied when the machine performs the "cognitive" functions that humans associate with other human minds, such as "learning" and "problem solving" through programming. Smart machines have also become increasingly capable of doing things at an impressive pace, ideally for the tasks entrusted with them and without mistakes.

ANFIS is a class of adaptive networks that functionally equivalent to fuzzy inference systems, where it works on the technology of hybrid learning algorithms, and which is known as Sugeno- Tsukamoto fuzzy models. ANFIS are combining FIS with neural networks to adjust the rule-based of fuzzy systems. The FIA system commonly uses two structures: Sugeno and Mamdani [18]. Sugeno method is selected in this research because it is computationally efficient, works well with linear techniques, and works well with adaptive optimization techniques, and it is well suited to mathematical analysis. Mamdani advantage is that it is intuitive and is well suited for the introduction of rights. But the drawback of Mamdani is computationally expensive because there is another set of parameters that is added to increase human interpretability [19, 20].

Network scalability adapts to a multilayered and sequential network feed and consists of serial nodes connected by connected connections, as each node has certain functions in the incoming signals to generate the output of a single node. Each connector determines the adaptation of the signal flow direction from node to another network. Every weight is linked with the correlation. And specifically, to increase, the network configuration is adapted to a fixed node on the receiving signals to generate a single output node, and each node has a specific function with adjustable bases. By replacing these parameters, the properties and functions of the node as well as the general behavior of the network to adapt, are replaced. Figure 6 displays that the system architecture is collected of five layers, quasi- fuzzy layer, creator layer, normalize layer, fuzzy layer and total resultant layer. The input-output for a special set of parameters, and data models of the fuzzy inference system mode Which is adjusting the function of organic parameters (modified) Using the propagation algorithm alone or in flipping by using the least squares type. The prime Target of ANFIS is to calculate the ideal results for fuzzy parameters of the conclusion system are plotted by applying a learning algorithm. The parameters to be improved in ANFIS are hypothesis parameters. These criteria define the form and physiology. In order to reduce the measurement error, any of the multiple optimization measures can be applied after forming the MFs.

Data modeling information is taken and learn from fuzzy parameter method. we have tow inputs x and y and one output f on adjustment of our system. Let's check in first class Takagi, Sugeno and Kang (TSK) fuzzy inference system contains two rules [20]:

$$\text{Base 1: If } (x \text{ is } A1) \text{ and } (y \text{ is } B1) \text{ then } f1 = p1a + q1b + r1 \tag{1}$$

$$\text{Base 2: If } (x \text{ is } A2) \text{ and } (y \text{ is } B2) \text{ then } f2 = p2a + q2b + r2 \tag{2}$$

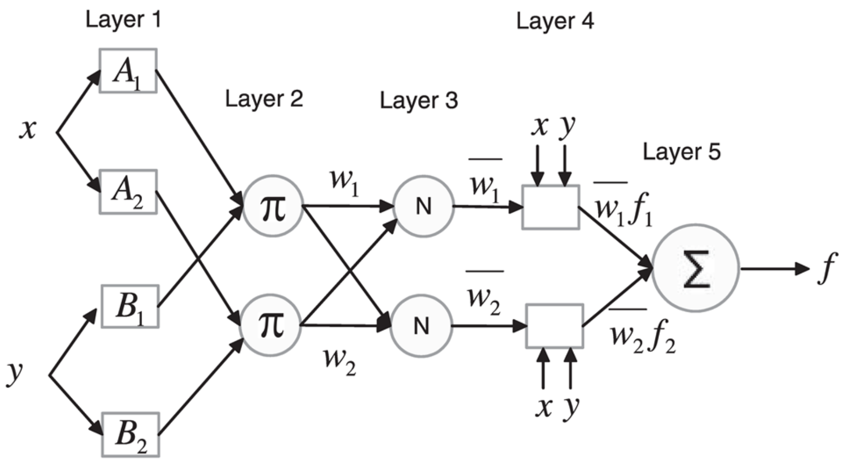

Fig. 6. The basic system architecture and Layers of ANFIS.

2.4. Hybrid Learning Algorithm

The Hybrid systems combine intelligent fuzzy logic (FL), Neural Networks (NN), genetic algorithms (GA), and Expert Systems (ES) are proving effective in a wide range of problems in the real world. Each smart technology has a certain mathematical property (such as the ability to learn and interpret decisions) that make them particularly suitable for the types of problems and not for others. For example, while the neural networks are good at recognizing patterns, they are not good at explaining how they reach their decisions. Fuzzy systems, which can be the mind with information is accurate and uncertainty, and good at explaining their decisions, but they cannot get the rules that are used to automatically make those decisions. Constraints are the main driving force for the generation of Crossbred intelligent systems, as two or more ways are combined to overcome the limitations of individual techniques. Crossbred intelligent systems are very important by viewing their applications in a variety of areas in their nature. Different types of treatments vary depending on the types of areas, the amount of complexity they contain and the many problems in them When we have a representation of complex problems and suppose that we have two problems that fall within the sub-troubles (such as treating and logical sequence of events) Refers to the task, Through the tests and use of the neural network and the integration of expert analysis in a sequential manner, solutions can be found for these tasks separately. The intelligent use of hybrid systems is currently expanding very rapidly with pre-designed successful software in many applications and areas such as various operations, engineering and architectural designs, economic trading, stocks, credit assessment, medical diagnosis and simulation.

Geometrically the standard values of ANFIS standards are determined by a mixed learning algorithm, of which we have already mentioned. As it is a way of estimating the lower squares (LSE) and the decline of the reverse gradient of the exercises. In the anterior passageway, the previous parameters are assumed constant while the parameters generated by the LSE algorithm are determined. In the backward path, the parameters that come are non-volatile and the previous parameters are determined by the back-propagation algorithm by descending the gradient.

The main steps of the proposed methodology are:

1. The first step involved gathering ECG data from publicly available databases, such as the MIT-BIH Arrhythmia Database. This dataset contains annotated ECG recordings representing various cardiac conditions, including normal and abnormal heartbeats. The selection of diverse and high-quality data is crucial for training and validating the classification algorithms effectively.
2. Once the data was collected, preprocessing was performed to enhance signal quality. This included:
   - Filtering: High-frequency noise was removed using bandpass filters, which help isolate the frequency range of interest in ECG signals.
   - Normalization: The ECG signals were normalized to ensure consistent amplitude levels across different recordings. This step is essential to reduce variability caused by differences in electrode placement and patient physiology.
   - Segmentation: The continuous ECG signals were segmented into individual heartbeats (windows) for analysis, allowing for focused classification of each beat type.
3. Feature extraction is a critical phase where relevant characteristics of the ECG signals are identified. Techniques employed included:
   - QRS Complex Detection: The Pan-Tompkins algorithm was utilized to detect QRS complexes, which are pivotal in identifying heartbeats.
   - Time-Domain Features: Features such as RR intervals, heart rate variability, and amplitude measurements were extracted from the segmented beats.
   - Frequency-Domain Features: Power spectral density analysis was conducted to examine the frequency components of the ECG signals, providing additional insights into heart rhythm characteristics.
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   - Frequency-Domain Features: Power spectral density analysis was conducted to examine the frequency components of the ECG signals, providing additional insights into heart rhythm characteristics.
5. The performance of the ANFIS model was compared against traditional machine learning algorithms such as SVM and decision trees. This comparison aimed to highlight the advantages of using ANFIS in terms of classification accuracy and interpretability. The entire methodology was implemented using MATLAB. MATLAB provided a robust environment for signal processing and machine learning tasks, enabling efficient data manipulation, algorithm implementation, and visualization. After classification, results were analyzed to determine the effectiveness of ANFIS in detecting various arrhythmia. The findings were discussed in relation to existing literature, emphasizing improvements in diagnostic accuracy and potential clinical applications.

To track tracking the ECG signal path, the primary signal based on P.Q.R.S and T waves is processed as an essential part as shown in Figure 7 and is filtered and clarified by noise. The filtration includes both a low pass filter and high pass filter. Low pass filter works to filter out unwanted noise such as power noise. The power noise is about 60 Hz. The high-pass filter is used to rotate or center the signal at zero-volt level to extract the true amplitude of the different parts of the signal accurately and compare the results with a standard signal and tracking signal parts. For example, P wave amplitude with an ECG signal can be drawn and compared to other P wave bands from the standard wave. In comparison, the level of deviation in the signal can be determined. This applies to the rest of the S.Q.R & T signal.

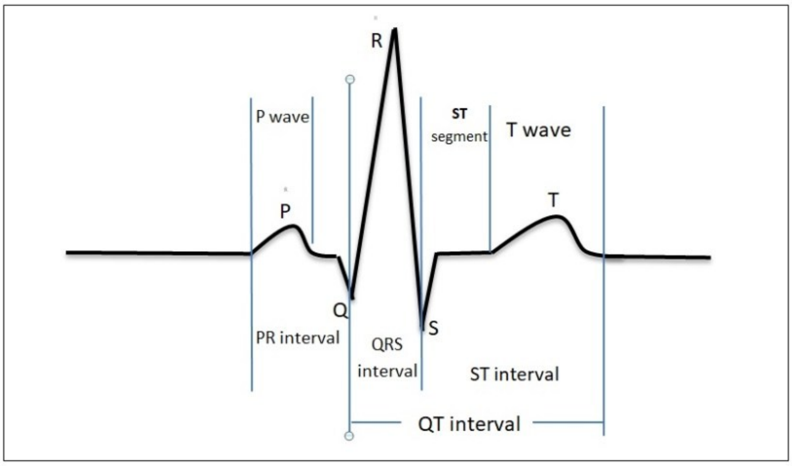

Fig. 7. Time tracking points for the heart signal.

This brief review of the image-denoising literature focuses on the scenario of additive white Gaussian noise. The significant achievements in this field, which have been studied over several decades, are highlighted, along with an exploration of recent developments in the literature and the introduction of deep learning algorithms. The emergence of deep learning algorithms is also discussed. After reviewing the relevant published material, several unresolved issues and questions are brought to the attention of the image-denoising community. This methodology section aims to provide a complete understanding of the methodologies reviewed, offering detailed implementation information and comparing the computing requirements of different denoising algorithms. This analysis is useful for selecting the appropriate methods based on the needs for denoising performance and computing efficiency.

The increase in input features clearly increases the system's ability to classify the tone. The input features of the ECG signal can be extracted by taking several data from the PhysioBank ATM database which we will work on them in the study of proposed models. Figure 8 presents a general Schematic how to configure the ECG signal and the kind of heartbeat.

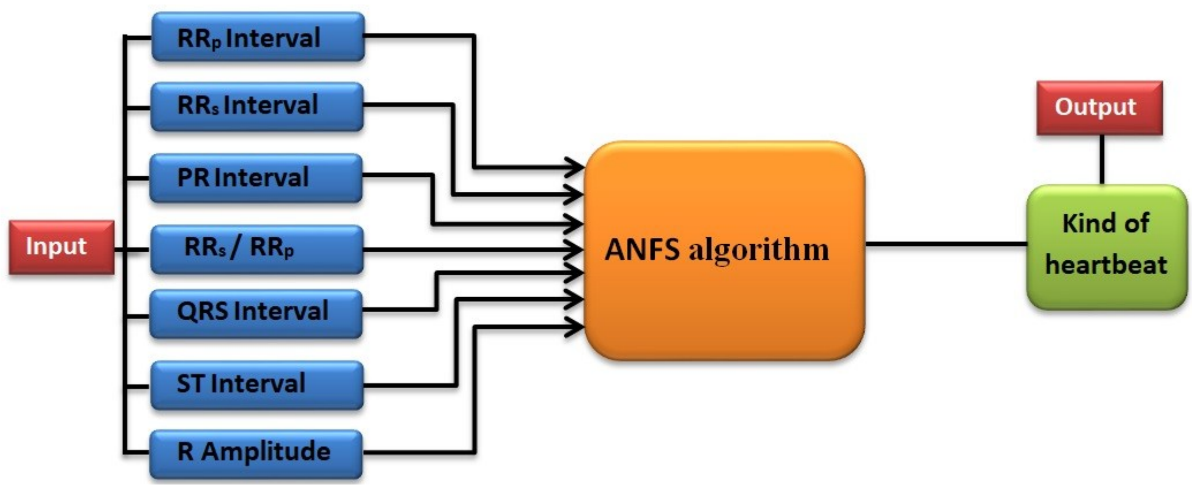

Fig. 8. Schematic how to configure the ECG signal and the kind of heartbeat.

3. Results and Discussion

System inputs consist of signal properties. Either property can be illustrative or calculated. The input features consist of the time characteristics and capacitance of ECG heartbeat (amplitude). The strikes are classified as normal, PVC, APC, LBBB, RBBB and Paced. Where the left side displays the seven input features that are used. Inputs for heart signals vary based on heart rate. Note that the normal heart rate according to international medical measurements is between 60-100 beats per minute (beats per minute). Table 1 shows a list of seven inputs that are classified as the formation of the ECG signal and analyzed via ANFIS.

Table 1. The information of the ECG signal of the proposed method.

	RR_p sec	RR_s sec	PR m_{sec}	RR_p/RR_s	QRS m_{sec}	ST m_{sec}	R Amplitude mv
Normal	0.6-1.2	0.6-1.2	120-200	1	80-100	80-120	1.5-2
PVC	<0.6	>1.2	Nr	>1	>120	Nr	<2
APC	<0.6	>1.2	Nr	>1	<80	Nr	>2
LBBB	Nr	Nr	Nr	Nr	>120	Nr	Nr
RBBB	Nr	Nr	Nr	Nr	>120	>120	Nr
Paced	Nr	Nr	>280	Nr	>120	Nr	>2

The results of the QRS are taken and determined in three stages. Samples of ECG signals were taken from the online database known as MIT-BIH arrhythmias from a physionet network. ECG signals were processed from the database to remove power line noise and high frequency interference. The deviation of the data examined and examined is then diagnosed and determined. And compare the deviation indicators that act as an input to distinguish the location of the error with the standard waves by entering the algorithm then the neural network is applied to the system training.

We have multiple ways to detect the QRS compound. One of these methods is another function that uses an algorithm to detect the beginning of a complex QRS and the displacement of the ECG signal, and that is the Pan-Tompkins algorithm.

The Pan-Tompkins algorithm works on discovery of QRS composite and T intervals based on digital analyzes of tilt, width and amplitude. The boundaries are periodically adjusted to adapt to QRS shape changes and heart rate at all points of the signal. In the MIT-BIH arrhythmia calculations, the algorithm achieved success in detecting 99.63 percent of heart rate. The disadvantage of this method is that the threshold technique is only feasible if the heart rate is normal. For arrhythmias case, two thresholds are reduced to increase detection sensitivity to avoid loss of correct heartbeat.

The main steps and scheme of the Pan-Tompkins algorithm to detect QRS complexes. As for all transport functions used in this algorithm they are.

- DC drift and normalization are carried out. The signal is subtracted through the total meaning of the signal and then normalized in each sample. This eliminates the signal along the zero-volt base line.
- The digital pass-wave filter is then made up of a series of low pass filters and a high pass filter with a passband of 5-15 Hz to the signal. This reduces the effect of noise resulting from muscle movement.
- It is passed over a derived filter to provide complex QRS regression information. The quadratic function is then applied to make all the points of the data regular, and it expands the non-linear output of the derived data with a focus on the higher frequencies. Where the quadrature occurs when it is squaring each point in the signal point by a point.

The quadrature function also provides further attenuation to the other ECG signal, making the QRS complexes as positive peaks in the signal, whatever their polarity in the original ECG recording. The main drawback of this approach is that by varying ECG squaring, the normal QRS peaks of small size and asynchronous peaks are reduced with a lower gradient in the conversion output. The ECG signals, their order, classification, and the type of disturbance are found in each signal from the MIT-BIH database are shown in Table 2.

Table 2. The ECG signals, their sequence, classification and kind of disturbance on each ECG signal on MIT-BIH.

ECG signal on MIT-BIH Record	Normal rate	PVC	APC	LBBB	RBBB	Paced beats
100	2239	1	33	0	0	0
101	1860	0	3	0	0	0
102	99	4	0	0	0	2028
103	2082	0	2	0	0	0
104	163	2	0	0	0	1380
105	2526	41	0	0	0	0
106	1507	520	0	0	0	0
107	0	9	0	0	0	2078
108	1739	17	4	0	0	0
109	0	38	0	2492	0	0
111	0	1	0	2123	0	0
112	2537	0	2	0	0	0
114	1820	43	10	0	0	0
115	1953	0	0	0	0	0
116	2302	109	1	0	0	0
117	1534	0	1	0	0	0
118	0	16	96	0	2166	0
119	2034	3	2	0	0	0
121	1861	1	1	0	0	0
122	2476	0	0	0	0	0
123	1515	3	0	0	0	0
200	1743	826	30	0	0	0
201	1625	198	30	0	0	0
202	2061	19	36	0	0	0
203	2529	444	0	0	0	0
205	2571	71	3	0	0	0
208	1586	992	0	0	0	0
209	2621	1	383	0	0	0
212	923	0	0	0	1825	0
213	2641	220	25	0	0	0
214	0	256	0	2003	0	0
215	3195	164	3	0	0	0
220	1954	0	94	0	0	0
222	2062	0	208	0	0	0
223	2029	473	72	0	0	0
228	1688	362	3	0	0	0
230	2255	1	0	0	0	0
231	314	2	1	0	1254	0
233	2230	831	7	0	0	0
234	2700	3	0	0	0	0

The training and verification results for six test models of the ANFIS are shown in Table 3.

Table 3. The training and verification of results for six test models for the ANFIS.

ANFIS models	RP	RN	LP	LN	Accuracy (%)	Sensitivity (%)	Quality (%)
1	35	175	0	0	100	100	100
2	32	158	3	17	90.48	65.31	98.14
3	34	175	1	0	99.52	100	99.43
4	34	175	1	0	99.52	100	99.43
5	34	175	1	0	99.52	100	99.43
6	34	175	1	0	99.52	100	99.43

4. Conclusion

Intelligent Algorithmic Approaches to ECG Signal Classification in Heart Disease Detection demonstrates significant advancements in the automated analysis of cardiac signals, particularly through the application of ANFIS. The study successfully illustrates how intelligent algorithms can enhance the accuracy and efficiency of ECG signal classification, which is crucial for timely diagnosis and management of heart diseases. The results indicate that ANFIS outperformed traditional classification methods, achieving high accuracy rates in identifying various arrhythmias, including APC, PVC, LBBB, and RBBB. This improvement in diagnostic capability is particularly important given the high mortality rates associated with undiagnosed heart conditions. By automating ECG analysis, the reliance on expert cardiologists can be reduced, allowing for quicker assessments and interventions. Moreover, the methodology employed encompassing data collection, preprocessing, feature extraction, and model training demonstrates a comprehensive approach to handling ECG signals. The use of ANFIS not only provides robust classification results but also maintains interpretability through fuzzy logic rules, which can be easily understood by clinicians. Despite these advancements, challenges such as data imbalance and computational resource requirements were noted. Future research could focus on addressing these limitations by integrating larger datasets and exploring hybrid models that combine the strengths of various machine learning techniques. Overall, this study contributes valuable insights into the field of computational intelligence in cardiology, paving the way for improved diagnostic tools that can significantly impact patient care and outcomes.

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