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Machine Algorithm for ECG-Based Heartbeat Monitoring and Arrhythmia Detection

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Abstract：A cardiac arrhythmia is a condition where the heartbeat is irregular and either too fast or too slow. It is caused by malfunctioning electrical impulses that synchronize the heartbeats. Some severe arrhythmia diseases can result in sudden cardiac death. Therefore, the main objective of electrocardiogram (ECG) research is to accurately identify arrhythmias as potentially fatal in order to provide an appropriate treatment and save lives. Waveforms known as ECG signals (P, QRS, and T) show how the human heart moves electrically. Each waveform's duration, structure, and the separations between its many peaks are used to detect cardiac issues. The parameters of the AR signal model are then determined by applying the signals' autoregressive (AR) analysis to a particular selection of signal attributes. The training dataset offers high connection categorization and heart issue detection for every ECG signal by neatly separating groups of extracted AR features for three different ECG types. To improve the evaluation of ECG data, a novel method based on fractional Fourier transform (FFT) algorithms and two-event-related moving averages (TERMAs) is proposed. Researchers may find this paper useful in analyzing the most advanced methods currently used for arrhythmia identification. Cross-database training and testing with enhanced features is a feature of our proposed machine learning methodology.

1. Introduction

All The electrical activity of the heart is measured by the electrocardiogram (ECG). In many cases, examining the ECG signal may help identify potentially fatal heart conditions. These researchers usually struggle to identify and diagnose many illnesses, including arrhythmias, which are defined as an elevated heart rate or a disturbance in a normal person's heart rate [1]. An aged heart, medications, metabolic problems, and disease can all contribute to irregular heart rhythms. One of the most deadly arrhythmias is sustained ventricular arrhythmia, which is often brought on by damaged heart muscle. About 31% of all fatalities worldwide are attributable to cardiovascular disease (CVD), making it the leading cause of death globally. The heart is an organ system with a cone shape that pumps blood to the inside tissues at regular intervals [2]. An obstruction in the coronary arteries, which supply the heart with blood and oxygen, causes a heart attack.

The World Health Organization states that CVDs are the primary global public health issue. In recent years, a number of programs and policies have been implemented in more diverse areas, providing resources, strategies, and tools to reduce the incidence of both first and recurrent cardiovascular events. Ultimately, the ECG has emerged as the most often used biosignal for CVD early diagnosis [3]. The ECG is used to diagnose various cardiac conditions and abnormalities since it is a schematic representation of the electrical activity of the heart. ECG electrical impulses have been used by physicians to diagnose heart issues, such as arrhythmias and heart attacks, for over 70 years. An ECG signal with complex P, QRS, and T waves is displayed in Figure 1.

2. Neuroscience and Computational Intelligence

QRS is inexpensive and safe. However, jumps in the ECG readings were known to be caused by artifacts, which included noise and other factors [4]. External electrical interference, electrode mobility on the body, and patient movements are examples of these artifacts.

A method based on the TERMA fusion and fractional Fourier transform (FFT) is proposed to address the drawbacks of the previously stated algorithms and produce better outcomes. Moving averages (MA) are helpful in identifying signals that make up intricate events, and TERMA is mostly utilized in economics to differentiate between different trading metrics [3]. Therefore, ECG data that contains events like T waves and P, QRS complex can be subjected to these averages. After a certain period of time, these waves continue on their own. The high variability in the P, QRS complex, and T waves makes time-frequency research important as well. This illustrates how these waves can be found using time-frequency studies and moving averaging. Additionally, it was shown that the proposed method in this work performs noticeably better than the current methods.

Several popular classification algorithms are used to classify the model parameters, which are used as ECG signal characteristics. The findings demonstrate that these characteristics are accurately classified and identify a range of heart illnesses and are well-separated in the recovered space [5]. Furthermore, distinct persons were identified from recorded ECG signals using sets of retrieved AR values. According to preliminary results, this approach has the potential to be applied in a variety of biometric scenarios. The technique utilized to obtain and classify those attributes, together with some results for arrhythmia detection and patient task information, is covered in the remaining research [6]. Finding and describing any CVD in an ECG signal is the next challenge. The two stages of the classification process are feature extraction and classifier model selection. Many researchers have concentrated on the categorization of ECG signals using a database of MIT-BIH arrhythmias. A range of preprocessing models, feature extraction techniques, and classifiers were employed in earlier studies, some of which are discussed in this study [7]. Multilayer perceptrons (MLP) have been used in classification techniques, and the discrete wavelet transform (DWT) is used to obtain features such as the R peak and RR interval. Similar to this, db4 DWT is used to identify the R peak region and RR interval; to recognize ECG signals, a feedforward neural network (FFNN) with backpropagation is created. Several classifiers, such as support vector machines (SVM), neural networks, AdaBoost, and Naive Bayes, were used in the classification process [8].

2. Review of Literature

Heart failure, cardiac arrhythmias, and sinus rhythms were among the abnormal heartbeats that were assessed in the study in [9]. An essential and popular tool for identifying and categorizing cardiac irregularities is the electrocardiogram (ECG). In order to diagnose cardiac abnormalities, an ECG signal examines the electrical activity of the heart and generates waveforms. As a result of this research, arrhythmias can be classified more accurately. The machine learning technique employed in this work is a shorter SVM classifier with discrete wavelet transform (DWT). Seventy-three percent of the composite signals from the MIT-BIH and BIDMC databases are split 70:30 across training and testing sets. DWT was utilized to extract 190 characteristics in total. The obtained features were classified using DWT as a solution SVM classifier because of its ability to change the window size based on frequency. A testing set was employed for analysis, and a model with a 95.92 percent performance accuracy was used to depict the outcomes. Heart-related diseases (CVDs) are the largest cause of death worldwide, accounting for a significant portion of deaths during the past few decades, according to [10]. Numerous academics have employed a range of machine learning algorithms in recent years to assist healthcare providers and the medical sector in diagnosing heart-related issues. To sum up, this study offers a summary of many models that concentrate on these techniques and approaches. Decision trees (DT), support vector machines (SVM), k-nearest neighbor (KNN), random forest (RF), ensemble models, and Naive Bayes are well-liked models, especially by scholars.

A sophisticated combination of pathological and clinical data was used in [11] to identify heart disease. This complexity has piqued the attention of researchers and clinical practitioners in creating an effective strategy for predicting the presence of heart disease. This study presents an algorithm for estimating the presence of heart disease based on clinical data. This method consists of three steps. Select 13 important clinical characteristics at the outset, including age and gender, the type of chest pain, treetops and cholesterol levels, blood sugar levels during fasting, resting electrocardiogram, maximal heart rate, exercise-induced angina, old peak, and slop. An artificial neural network (ANN)-based algorithm is developed to identify heart illness based on these clinical factors. About 80 percent of the forecasts are accurate. A user-friendly heart disease prediction system (HDPS) was created as the last stage. It is possible to predict a patient's cardiac status with accuracy thanks to approaches. The HDPS system, a groundbreaking technology that may be used in this approach, was created as a result of this effort.

According to [12], heart disease (HD)-related death and morbidity are increasing in contemporary society. Medical diagnosis automation would be very helpful as it is a crucial but challenging task that needs to be done accurately and effectively. Because not all physicians are equally skilled in every discipline, there is a scarcity of physicians in many regions of the world. An automated medical diagnosis system would not only improve medical care but also lower costs. A coactive neuro-fuzzy inference system (CANFIS) was used in this study to develop a novel method of preventing heart disease. A descriptive fuzzy-based approach and an autonomous neural network system are combined in the proposed CANFIS for new diagnostic analysis. The suggested CANFIS algorithm is proven to have a significant ability to diagnose cardiac disease based on its accuracy rate and training efficiency.

A hybrid method for choosing the best characteristics of cardiac arrhythmias and classifying them is presented in the study in [13]. The Decision Tree (DT) technique was used to extract the feature in order to organize and construct the system, and the Genetic Method was used to select the features in the proposed model as efficiently as possible. The 16-class collection of arrhythmias is classified using the planned technique into normal and pathologic categories. Selectivity, sensitivity, accuracy, and mean Sen-Spec characteristics, along with the UCI arrhythmia database, can be used to compare the effectiveness of the proposed strategy to that of comparable methods. When compared to comparable methods, the accuracy, sensibility, average sensitivity, and specificity metrics are significantly improved by the effectiveness of the proposed method in both two-class and 16-class modes. Our method demonstrated 86.96 percent accuracy, 88.88 percent sensitivity, and 86.55 percent mean Sen-Spec parameters for the two-class model, and for the 16-class model categorization, 78.76 percent, 76.36 percent, and 78.69 percent. The UCI arrhythmia database's top values are those mentioned above.

3. Techniques

As seen in Figure 2, the ECG classification system created in this article can be broken down into four main phases. The stages are as follows:

(i) ECG preprocessing

(ii) QRS and segmentation signal detection

(iii) Parameter extraction

(iv) Clustering and categorization of extracted parameters

3.1. Preprocessing of ECG.

Drift, a needless minimum-frequency movement in the ECG, is the preprocessing objective stage. It can interfere with signal analysis and lead to inaccurate and deceptive clinical interpretation. Although it usually has a spectrum content much below 1 Hz, intense exertion may cause higher frequencies to be present.

One of the most common methods for eliminating baseline drift and excessive noise from ECG measurements is filtering. In the past, both FIR and IIR filter types worked well for this task; the 0.8 Hz and 40 Hz ranges, respectively, had lower and higher cutoff rates. Avoid using a cutoff frequency higher than 0.8 Hz since it has been shown to drastically change the ECG waveform. In this study, bandpass filtering is used to reduce and get rid of the noise disturbance that typically shows up in ECG data. The cutoff wavelength of the bandpass ECG filter is 40 Hz, while the lower cutoff frequency is 5 Hz.

3.2.QRS detection.

The most important component of the ECG signal was the QRS complex. The P and T waveforms, as well as the QRS complex's start and delay, are all specified for such a complex. A filtering step followed by an average based on a threshold value is the foundation of the majority of QRS recognition algorithms [15]. Based on the top position of the ECG signal, this threshold is utilized to distinguish between the background and the QRS complex. Additional machine learning-based methods include the P-spectrum method, which is a potent means of identifying periodicity in data discontinuities.

3.3. The parameter is extracted.

At the next level of the system, each ECG signal is detected individually, followed by the application of AR modeling of two or more consecutive ECG beats using the discrete variation of an AR signal model of order j, AR(j). The variance of forecast errors as a function of basic functions j is examined in order to identify the order j of each dataset. In this investigation, modeling two successive ECG beats found using the filter bank method as described in the previous section produced positive findings [16]. In the design and system phase, the estimated model's coefficients are then used as classification signal characteristics.

The classification model uses xf(f ⁽ 1, 2,..., j) and $\varepsilon(v)$, which are model coefficients, also known as autoregressive parameters. $\varepsilon(v)$ is a white noise sequence, technology process with a zero mean, and variance $\sigma 2$. With the actual output $k(v)$ predicted from the previous $(j-1)$ AR processes target value, equation (2) now treats the computed autoregressive model as a p-point predictions filter.

The first step in the ECG analysis procedure was to reduce baseline deviations and other patterns in a raw signal caused by power line intrusions and artifacts [14].

3.4. Categorization.

Several classification approaches were used to identify and categorize the gathered ECG signal features. This study is distinguished by the multidimensional matrices that contain the determined autoregressive parameters for each beat of the recorded ECG data. Because of its simplicity, the k-nearest neighbor method is one of the most often used techniques in bioinformatics and other domains; however, care must be taken while selecting the model of order k as suitable dimension measurements. In order to proceed to the next phase of this investigation, linear (LDA) and quadratic (QDA) discriminant analysis classifiers used in a different bioinformatics application were used to address and evaluate the electrocardiography identification of patient features.

3.5. Heartbeat Classifier.

The recommended heartbeat classifier is developed using an echo state network (ESN). Based on morphological characteristics, it separates the heart rates from the examined ECG data into two groups: VEB+ and SVEB+. SVEB+ was the classification for both normal (N) and supraventricular ectopic (S or SVEB) heartbeats. These heart rates have a regular morphological profile and a supraventricular source, as opposed to VEB + heart rates, which have a ventricular source or aberrant morphology. The VEB + category (F) contained fusion beats and ventricular ectopic beats (V or VEB).

The two phases can be distinguished from one another:

(i) Stage 1: The initial stage of analyzing an ECG recording includes feature extraction, filtering, heartbeat segmentation, and heartbeat detection. We incorporate morphological and temporal pauses between heart rates in this approach.

(ii) Stage 2: classification between SVEB+ and VEB + - classes. We use an ensemble of ESNs with ring topology to carry out this classification task. As seen in Table 1, we discuss the categorization method in phase two in more detail later in the paper.

3.6. ECG processor and feature extraction.

To categorize arrhythmias, a small amount of pre-processing of the original ECG records is necessary. This framework includes the fundamental techniques for analyzing ECG recordings.

3.6.1.ECG filtering.

A bandwidth] (Hz) ∈ [0.5, 35] is used to process all ECG recordings in order to correct the foundation and remove unwanted high frequency disturbances. Using the traditional method, a 12th-order limited impulse response filter (35 Hz, at 3 dB point) and a Butterworth high-pass filter (cutoff frequency of]c ⁽ 0.5 Hz) were used.

3.6.2. ECG signal resampling.

The monitoring frequency used to examine ECG transmissions was 260 Hz. The MIT-BIH AR dataset (350 Hz) is normalized to 260 Hz using the PhysioToolkit application tool, while the AHA dataset (260 Hz) is maintained at its typical recording frequency.

3.6.3 How to calculate the RR Interval.

The time between successive heart rates is known as the RR interval. The RR interval associated with heartbeat i, RR(i), represents the duration comparison between heartbeat i and the previous heartbeat (i−1).

3.6.4. Detection of heartbeats.

The location of heart rates was estimated using annotated coordinates provided by datasets. In the MIT-BIHAR database, the annotating position is located at the top of the localized edges of the QRS complex. This study is not concerned with beat identification. Additionally, very successful automatic beat recognition systems have been reported.

3.6.5. Normalization of Heartbeat Segments.

All segmented heart rates are within the usual range [1, 1]. The signal produced by this scalability technique is independent of the original ECG recordings' frequency.

3.6.6. Segmentation of heartbeats.

The ECG signals are segmented according to each database's designated position. The segmented heart rhythms are centered on the annotated location and span 250 milliseconds (65 samples per second at 250 Hz).

After the ECG data are processed, each heart rate is described by a set of characteristics. One of the main goals of choosing parameters for this system is to avoid challenging features with high computational costs because we wish to build a quick and real-time heartbeat categorization. Consequently, our focus is on simple techniques for obtaining attributes. The real waveform of each heartbeat between the heart rate points is shown in our example. An equal number of samples from each side of the beat identification position supplied the actual information for each beat. At the end of the preprocessing and feature extraction phase, each pulse is shown as a d dimensional vector, with 65 morphological features—basically a sampling of the ECG waveform around the point indicated for each heart rate—and three characteristics pertaining to the RR intervals. This d − dimensional vector (d ⁽ 62) is used as input in the categorization technique.

3.7. ECG waveform:

ECG patterns are indications of the electrical system of the heart and are crucial to the diagnosis process when examining physical health. The P wave, QRS complex, and T waveforms make up a typical ECG trace. Noise and artifacts are removed using the conventional wavelet transform-based filtering method. The ECG signals were identified and the presence of CVD was assessed using a combination of machine learning techniques, TERMA and FFT, to increase detection accuracy. The specific responsibilities are covered in further detail in the following subsections.

3.8. Filtering signals.

Because the ECG signals were nonstationary, the resonance frequency fluctuated over time. Additionally, the ECG signal contamination from noise and objects had a time-dependent probability density and was nonlinear. Traditional Fourier transform methods cannot do time localization; however, DWT can. DWT is hence better equipped to handle non-stationary signals [18]. To start, the average drift is removed using DWT. The first step is to calculate the wavelet's core frequency, or Rc (also called the Fc factor), which is dependent on how closely the signal resembles the selected waveform and ranges from 0 to 1.

Electrical system and are crucial to the diagnostic process used to assess physical wellness. Every ventricular contraction produces a P wave, QRS complex, and T wave, which make up a normal ECG trace [17]. When the heart's typical electrical impulse pattern is disturbed, arrhythmias—abnormal heartbeats—occur. Both the lower and upper chambers of the heart can experience arrhythmias, however ventricular arrhythmia is the most common.

As mentioned before, in order to detect P, QRS, and T waves, signal noise and artifacts must be removed. to determine P, where a and Rs stand for the gauge and selection frequency of the ECG signal, respectively. Most of the baseline drift

takes place at 0.5 Hz. With (3) for the MIT-BIH Fs 360, it will be simple to calculate the scales corresponding to different pseudo-frequency. Decomposition should occur up to scale 9, which is equivalent to Ra 0.5. The ECG signal is thus split into approximate and detailed coefficients up to scale 9 using the db4 wavelet. The estimated coefficients associated with the drift baseline were eliminated, and IDWT was used to rebuild the signal in order to discover a baseline signal that was drift-free.

3.9. Fusion Algorithm for P and T Peak Detection.

To find the P and T peaks, TERMA uses a sophisticated threshold. We were able to reduce the total processing complexity of the method by using a lower threshold. The algorithm's initial step eliminates the R peaks to make the P and T peaks stand out more. The R peak value was set to 0 in the noise-free signal since the 30 samples (0.083 s) were significantly earlier than the R peak and the 60 samples (0.166 s) [20]. The likelihood of the P and T waves occurring within the designated interval was almost zero for any CVD. After the QRS interval was eliminated, the signal was substituted in a time-frequency plane using the FFT to increase the P and T peaks. As shown in Figure 5, blocks of interest were created using two moving axes in the same manner as in the subsequent step:

The arrangements [19] demonstrate multiplying, chirp inversion, and another chirp multiplication. Higher values of rotation correspond to a closer approach to the transmitter's resonant frequency, while lower values correspond to a move away from the signal's resonant frequency, which is equivalent to a move closer to the signal's temporal domain. In order to recognize R peaks, time localization is essential. Through the use of hit-and-trial methods, it was found that a parameter of α 0.01% correctly increases R peaks and makes them hard to identify. Following the use of FFT, each sample was squared, which further raised the R peak.

The P wave frequency determines W3, the QT interval determines W4, $d\ \sqrt[3]{\ }\ U3 - 1/2$, and $e\ \sqrt[3]{\ }\ U4 - 1/2$ W421. A fit person will have a P wave duration of (100 ± 20) ms and a QT interval of (400 ± 40) ms. A minimum window is utilized to account for the distinct characteristics of the arrhythmias rather than a standard size window to identify P waves. Instead of detecting the R peak, the measurements were simply the values of the subsequent moving average. If the original average was greater than the corresponding next moving average, one is allocated. If the zero is not allocated, a new vector is produced. A stream of irregular rectangular impulses is the result of this. Lastly, a threshold based on the PR, RR, and RT intervals was used to distinguish the generated blocks from blocks containing P and Tpeaks. If there is a gap between the block's greatest advantages and the closest R peak on the designated PR interval, the block's highest power is referred to as the P peak. The length of the QRS complex determines U1, and the length of the heartbeat determines U2, if the difference between the appropriate MA alone is represented as a moving average. The hit-and-miss method was used to find the ideal parameter value. The mean (μ) of the augmented signal is calculated and raised by factor (β). The output value, denoted by c ⁽ βμ, was applied to MAcyclic, generating threshold values. The pertinent threshold values were contrasted with the MAevent values. If MAevent(n) exceeds the nth condition, one is allocated. If zero is not supplied, a new vector is produced. This results in a stream of rectangular pulses with a nonuniform distribution.

4. Findings and Conversation

The four sections that make up this segment are devoted to the following topics: categorization, cross-database training and testing, peak detection, and arrhythmia recognition.

4.1. Arrhythmia Recognition. An ECG set of findings comprising three distinct ECG signal types has been used to evaluate the efficacy of the suggested system. The dataset included ventricular arrhythmia (VAR) from the MIT-BIH Malignant Ventricular Arrhythmia Database, arrhythmia (AR) from the MIT-BIH Arrhythmia Database, and normal ECG signals (NR) from Politecnico of Milano VCG/ECG Data on Young Normal Subject. Although each person's test only took a few minutes, each type was represented by 20 half-hour records of two-channel outpatient ECG data. AR parameters are generated for every extracted set of beats following the beat identification and signal separation processes. The performance of the classification program may be impacted by the quantity of AR parameters gathered for each team as well as the frequency of beats in each band. Two to four AR variables and one to five band beats were successfully classified. This illustrates how well the two beats per set performed in this investigation with AR order p values of two and three. The error levels for various AR-type orders for both preprocessed and raw ECG signals are shown in Figure 6.

Additionally, the size of associated feature clouds in AI feature space should be used to observe the fluctuation of retrieved variables. The ventricular arrhythmia cloud has the greatest variation and dispersion of picture features, whereas the dimensionality of the data cloud linked with daily ECG signals is rather small when comparing the variations of the information clouds to differentiate between the two arrhythmias.

4.2. ECG Peak Detection. Our proposed FFT-based method is used to find the P, R, and T peaks in the first part of the simulation, and the proposed methodology is verified on all 48 records in the MIT-BIH. Lead II (MLII) data is used in this re-search. Any of the following details will be useful for identifying the peak because our method is unaffected by the waveforms' magnitude.

4.3. Classification of CVD. The ECG signals are grouped according on their CVDs in the following section of the experiment. Thirty percent of the chosen features were retained for test results, and seventy percent were used to train a machine learning model for each simulation. Consequently, a number of features were extracted for categorization from the waveforms. Following the collection of features, the input ECG signals were classified as regular, PVC, APC, LBBB, RBBB, and PACE heartbeats using the SVM and MLP classifications.

5. Conclusion

In arrhythmia and ventricular arrhythmia, an automatic method for grouping ECG data into three categories has been introduced. A fusion method based on FFT and TERMA was introduced to identify the R, P, and T peaks. Conventional wavelet transform techniques were utilized to denoise the data, but the accuracy of peak identification was significantly improved by the addition of FFT to the TERMA approaches. In the MIT-BIH arrhythmia collection, the suggested peak identification performs the function marginally better than the TERMA algorithm in finding the R peak but much better in detecting the P and T peaks. The AR parameters that are used to classify each segment of the ECG signal into one of three possible categories are extracted using AR modeling after the pre-processing procedures. Excellent classification accuracy may be expected in the effective implementations of the proposed system, as evidenced by the highly split and well-categorized selected features and AR properties for sets of the two beats in the feature space. Additionally, CVDs had no effect on the effectiveness, in contrast to the TERMA approach. The PR and RT times are used as features of two ECG signals for classification after peak detection, and a classifier is built for cross-database testing and training.

References

[1] ECG-based heartbeat classification for arrhythmia detection," *Future Generation Computer Systems*, vol. 86, pp. 446–455, 2018.
[2] S. Sahoo, M. Dash, S. Behera, and S. Sabut, "Machine learning approach to detect cardiac arrhythmias in ECG signals: a survey," *IRBM*, vol. 41, no. 4, pp. 185–194, 2020.
[3] B. Vuksanovic and M. Alhamdi, "ECG based system for ar- rhythmia detection and patient identification," in *Proceedings of the ITI 2013 35th International Conference on Information Technology Interfaces*, Cavtat, Croatia, June 2013.
[4] K. Balaskas and K. Siozios, "ECG analysis and heartbeat classification based on shallow neural networks," in *Proceedings of the 2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST)*, Thessaloniki, Greece, IEEE, May 2019.
[5] K. Luo, J. Li, Z. Wang, and A. Cuschieri, "Patient-specific deep architectural model for ECG classification," *Journal of Healthcare Engineering*, vol. 2017, Article ID 4108720, 13 pages, 2017.
[6] Z. Han, S. Li, and H. Liu, "Composite learning sliding mode synchronization of chaotic fractional-order neural networks," *Journal of Advanced Research*, vol. 25, pp. 87–96, 2020.
[7] G. T. Taye, E. B. Shim, H.-J. Hwang, and K. M. Lim, "Machine learning approach to predict ventricular fibrillation based on QRS complex shape," *Frontiers in Physiology*, vol. 10, p. 1193, 2019.
[8] Y. Zhou, H. Liu, J. Cao, and S. Li, "Composite learning fuzzy synchronization for incommensurate fractional-order chaotic systems with time-varying delays," *International Journal of Adaptive Control and Signal Processing*, vol. 33, no. 12, pp. 1739–1758, 2019.
[9] C. Usha Kumari, A. Sampath Dakshina Murthy, B. Lakshmi Prasanna, M. Pala Prasad Reddy, and A. Kumar Panigrahy, "An automated detection of heart arrhythmias using machine learning technique: SVM," *Materials Today Proceedings*, vol. 45, pp. 1393–1398, 2021.
[10] V. Ramalingam, V. Ayantan Dandapath, and M. Karthik Raja, "Heart disease prediction using machine learning techniques : a survey," *International Journal of Engineering & Technology*, vol. 7, p. 684, 2018.
[11] A. H. Chen, S. Y. Huang, P. S. Hong, C. H. Cheng, and E. J. Lin, "HDPS: heart disease prediction system," in *Pro- ceedings of the 2011 Computing in Cardiology*, Hangzhou, China, September 2011.
[12] L. Parthiban and R. Subramanian, "Intelligent heart disease prediction system using CANFIS and genetic algorithm," *International Journal of Biological and Medical Sciences*, vol. 3, 2008.
[13] M. Ayar and S. Sabamoniri, "An ECG-based feature selection and heartbeat classification model using a hybrid heuristic algorithm," *Informatics in Medicine Unlocked*, vol. 13, pp. 167–175, 2018.
[14] V. Gupta, M. Mittal, and V. Mittal, "Performance evaluation of various pre-processing techniques for R-peak detection in ECG signal," *IETE Journal of Research*, pp. 1–16, 2020.
[15] G. Goovaerts, S. Padhy, B. Vandenberk, C. Varon, R. Willems, and S. Van Huffel, "A machine-learning approach for de- tection and quantification of QRS fragmentation," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 5, pp. 1980–1989, 2018.
[16] S. Celin and K. Vasanth, "ECG signal classification using various machine learning techniques," *Journal of Medical Systems*, vol. 42, no. 12, pp. 241–311, 2018.
[17] A. Salem, K. Revett, and El-Sayed A. El-Dahshan, "Machine learning in electrocardiogram diagnosis," in *Proceedings of the 2009 International Multiconference on Computer Science and Information Technology*, pp. 429–433, IEEE, Mrągowo, Poland, October 2009.
[18] Po-Ya Hsu and C.-K. Cheng, "Arrhythmia classification using deep learning and machine learning with features extracted from waveform-based signal processing," in *Proceedings of the 2020 42nd Annual International Conference of the IEEE En- gineering in Medicine & Biology Society (EMBC)*, pp. 292–295, IEEE, Montreal, QC, Canada, July 2020.
[19] T. Vijayakumar, R. Vinothkanna, and M. Duraipandian, "Fusion based feature extraction analysis of ECG signal interpretation–a systematic approach," *Journal of Artificial Intelligence*, vol. 3, no. 01, pp. 1–16, 2021.
[20] P. Tsinganos and A. Skodras, "On the comparison of wearable sensor data fusion to a single sensor machine learning technique in fall detection," *Sensors*, vol. 18, no. 2, p. 592, 2018.
[21] F. Y. Osisanwo, J. E. T. Akinsola, O. Awodele, H. Jo, O. Olakanmi, and J. Akinjobi, "Supervised machine learning algorithms: classification and comparison," *International Journal of Computer Trends and Technology*, vol. 48, no. 3, pp. 128–138, 2017.
[22] R. J. P. Princy, S. Parthasarathy, P. Subha Hency Jose, A. Raj Lakshminarayanan, and S. Jeganathan, "Prediction of cardiac disease using supervised machine learning algorithms," in *Proceedings of the 2020 4th International Conference on In- telligent Computing and Control Systems (ICICCS)*, pp. 570– 575, IEEE, Madurai, India, May 2020.
[23] S. Savalia and V. Emamian, "Cardiac arrhythmia classification by multi-layer perceptron and convolution neural networks," *Bioengineering*, vol. 5, no. 2, p. 35, 2018.