JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 05 Issue 02
2023
Research Article
https://doi.org/10.56979/502/2023

Novel framework for Efficient Detection of QRS Morphology for The Cardiac Arrhythmia Classification

Qurat-ul-ain Mastoi[1], Hira Farman[2], and Saad Ahmed[2*]

[1]Faculty of Computer Science and Information Technology, University of Malaya, Malaysia.
[2]Faculty of Computer Science, IQRA University Karachi, Pakistan.
[*]Corresponding Author: Saad Ahmed. Email: saadahmed@iqra.edu.pk

Received: July 31, 2023 **Accepted:** August 12, 2023 **Published:** September 17, 2023

Abstract: The abnormal conduction or disturbance in the cardiac activity is called cardiac arrhythmia except for sinus rhythm. Cardiac arrhythmias are placing a significant strain on the healthcare system as a result of the rising mortality rate in the world. According to the American Heart Association's (AHA) updated health data records, heart disease is the leading cause of mortality, with 17.3 million stated in the recent annual report. A cardiac specialist frequently uses an electrocardiograph (ECG), a non-invasive instrument, to identify heart arrhythmia. Currently, studies have been directed at employing computer-aided techniques to diagnose cardiac arrhythmia. However, due to the interpatient variability issues in ECG signal, QRS morphology is difficult to analyze as it is regarded as the primary characteristic because of its wide range of variances. In literature analysis, we have found that accurate detection of the QRS morphology using computer-assisted methods still is quite a challenging task due to the different variations. In the field of medicine, the biased results may cause ineffective detection of cardiac arrhythmias and can lead to the serious lives threat of patients. Moreover, human error and time constraints are two additional concerns associated with manual cardiac arrhythmia analysis. This research seeks to offer a novel methodology for the extraction of the QRS morphological feature (E-QRSM) to classify Premature Ventricular Contraction (PVC) arrhythmia from ECG signals. This would save the patient time and medical professional effort. The exact morphological features that are pertinent to the arrhythmia must be extracted, which is the most important and difficult part of the ECG signal analysis. In this study, a novel E-QRSM algorithm for categorizing PVC arrhythmias is presented. Since QRS segments are thought to be the primary component of PVC arrhythmia, these components are fed to the classifier. The studies were carried out utilizing the MIT-BIH arrhythmia benchmark dataset as a public benchmark to assess the effectiveness of our suggested E-QRSM approach. E-QRSM found that the proposed methodology's experimental analysis revealed that the novel algorithm delivers accurate and effective real-time analysis of QRS-related aspects with the conduction of aberrant rhythm in ECG data.

Keywords: Cardiac arrhythmia, Biomedical Signal Processing, feature extraction, data mining, and machine learning.

1. Introduction

An electrocardiogram signal is one of the primary sources for identifying cardiac activity. The disturbances in ECG signals is known as arrhythmia, which may cause severe heart disease, and the excessive nature of arrhythmia is considered as an alarming condition of emergency circumstances for the patient. Ventricular heartbeat is the common type of arrhythmia, it often occurs between the normal beat. The occurrence of ventricular heartbeat decides whether the arrhythmia is in the critical stage or non-critical stage. However, when it occurs repeatedly in ECG signals it might be life-threatening. To diagnose the ventricular heartbeat, it is necessary to monitor cardiac condition continuously using a long recording of ECG signals which is a quite tedious process and requires a lot of time and effort to detect the morphological changes in a heartbeat. Therefore, there is an immense need for efficient computer-aided methods for timely and accurate diagnosis of a critical heartbeat. In recent years, most of the studies focused on one-dimensional heartbeat data sets. Conventional methods are used to extract morphological features first to feed classifiers, for instance, the amplitude of waveforms, characteristics, and intervals of waves. BP neural network was proposed by [1] the authors used manual feature extraction methods, discrete cosine transform [2] were used to take the features from ECG morphology, and for classification, they used a probabilistic neural network. Artificial neural networks [3] were used to classify six categories of heartbeats from the ECG signal. Hybrid neural networks and feed-forward neural networks were proposed by [4] to classify the different types of beats and arrhythmia from ECG signals. Although extensive effort has been made in the literature, the objectives were to classify heartbeats and arrhythmia automatically. Some of the studies like [5],[6] used deep learning and machine learning techniques to classify arrhythmia and heartbeats respectively, but they failed to maintain high accuracy and their proposed systems were not efficient enough to implement in hardware devices. However, they focused generally on different types of heartbeats whereas each type of heartbeat has different characteristics. This paper aims to propose a novel methodology named E-QRSM for the extraction of only QRS morphology for the classification of PVC arrhythmia as the most critical heartbeat and associated with mortality, this statement motivates us to reduce the medical practitioner burden and early signs of cardiac morbidity can save the patient time and lives as well. QRS morphology is the most essential part of the ECG signal to analyze for PVC arrhythmia detection because most of the time it is irregular and has abnormal behavior in the ECG signal. (PVC) often occurs between normal heartbeats; therefore, it is a challenging task to properly identify using the relevant attribute. This study makes the following contributions

- To develop and implement the E-QRSM algorithm for PVC arrhythmia classification.
- To extract the relevant hidden information from ECG signals.
- Tune the RNN hyperparameters for cost-efficient classification.
- This study also performed an experiment using RNN for comparative analysis.

2. Literature Review

This section presents a comprehensive discussion of related work ECG is basically the graphical representation of the electrical activity of cardiac muscles during contraction and release stages. It helps in the determination of the cardiac arrhythmias in a well manner. Due to this early detection of arrhythmias can be done properly. In this study [1], a novel probabilistic brake pressure prediction approach for electric vehicles is created using multilayer Artificial Neural Networks (ANN) with the Levenberg-Marquardt Backpropagation (LMBP) learning algorithm. Using these two types of features, a support vector machine classifier is employed in this study [2] to cluster heartbeats into one of 15 or 5 groups. Based on the MIT-BIH arrhythmia database, the increased technique achieves an overall accuracy of 98.46% in the "class-based" evaluation strategy and 93.1% in the "subject-based" assessment strategy. These findings indicate that the increased technique outperforms state-of-the-art automatic heartbeat categorization methods. This work [3] investigates the topic of ECG pattern recognition. It refers to the classification and characterization of data patterns into preset classifications. The ECG signal analysis is a pattern recognition application. The waveform created by the ECG signal contains practically all of the information regarding the heart's activity. In this research, the ECG signal feature extraction parameters spectral entropy, Poincare plot, and Lyapunov exponent are studied. The study also incorporates an artificial neural network as a classifier for recognizing heart disease abnormalities. Efficient and quick electrocardiogram (ECG) beat categorization is a critical step in the deployment of real-time arrhythmia treatment systems. Convolutional neural networks are used in this study [5] to classify eleven different ECG beat types in the MIT-BIH arrhythmia database. The main evaluation method for detecting how various heart functions behave abnormally as a result of various cardiac disorders is electrocardiography. In this paper[6], we propose a computerized approach for the diagnosis of normal sinus rhythm, left bundle branch block (LBBB), right bundle branch block (RBBB), atrial premature beats (APB), and early ventricular contraction (PVC) on ECG signals using an assortment of convolutional neural network, or CNN and long short-term recall (LSTM). Their utilization of ECG segments with varying lengths from the MIT-BIT arrhythmia physio bank repository makes the strategy new. This research [7] offers a significant novel insight into the predicted classification of flattening MI T-wave individuals. The proposed solution [8] was created specifically for Medical Internet of Things (MIoT) devices, such as wearable wireless devices for ECG monitoring or ventricular heartbeat detection systems. The suggested model's performance was examined using the MIT BIH AR dataset, and it produced impressive results. Positive predictive value and sensitivity are 98.98% and 98.98%, respectively. The aim of the design work [9] is to achieve higher performance in terms of reliability and better diagnosis of patients through Peak detection. This study [10] used deep learning techniques to create a system of indicators for classifying different cardiovascular conditions. Using deep learning approaches, this study [11] created a diagnosis system for diagnosing various cardiovascular illnesses. In general, ECG arrhythmia can be diagnosed by its form. Because of the incidence of significant arrhythmias, a well-organized and strong CAD (computer-assisted design) system to precisely and automatically detect all forms of arrhythmias ECG signals gathered by Physio.net and keggar.com, the proposed methods were tested. PVCs are cardiac irregularities that can happen in people either with or without cardiovascular diseases. Using the RR-interval (the amount of distance across successive beats) retrieved from ECGs or from the heart pulse signal recorded by mobile devices, a method for searching for PVCs was built in this study work [12]. In this research [13], a fractional linear estimation (FLP)--based modeling approach for the complex of the QRS is proposed. In the area of QRS complex modeling, the research has demonstrated effectively that FLP modeling may be used as a supplement to LP analysis. In order to distinguish between unusual and usual morphological events of the ECG signals, this work[14]presented the fusion approach of dual event-related shifting averages (DERMA) with the fractionated Fourier-transform algorithm (FrlFT). This research [15] created an ECG monitoring module employing IoMT devices to acquire real-time datasets for experiments and extract relevant features from ECG signals. To foresee a PVC arrhythmia, the quickest extended version of the recurrent neural network (RNN) model cyclic echo state networks was used to classify ECG beats. In this study [16], flamingo optimizing. is used to create an efficient classification model for the categorization of cardiac disease. This research [17] created an ECG monitoring module applying IoMT devices to acquire real-time datasets for experiments and extract relevant features from ECG signals. To predict PVC arrhythmia, the quickest extended version of the recurrent neural network (RNN) model cyclic echo state networks was used to classify ECG beats. In order to identify research trends, problems, and alternatives for DL-based ECG arrhythmia grouping, a thorough assessment of the ECG record-keeping system, initial processing, DL technique, evaluation paradigm, performance metric, and code availability is undertaken in this study [18].

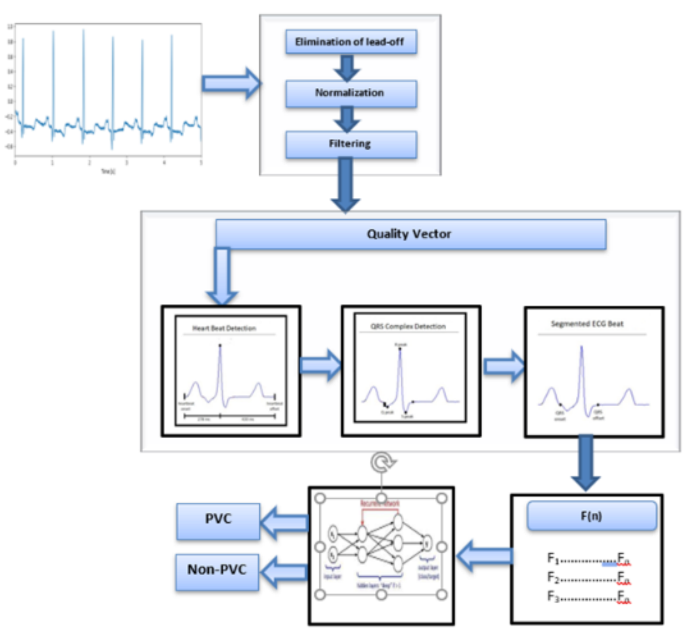

Figure 1. Representation of E-QRSM Methodology

3. Materials and Methods

The experiment was conducted on two public datasets see section 2, before proceeding to the practical; firstly, we preprocess the dataset to remove the noise contamination from ECG signals. Secondly, we developed the E-QRSM methodology for the extraction of exact QRS morphology and the complete cycle of beat. After the implementation of the proposed methodology of E-QRSM, the extracted features were used to feed the simple neural network classifier for the classification of premature ventricular cardiac arrhythmia. The overall procedure of our proposed methodology is depicted in Figure 1.

3.1. ECG Dataset Sources

The development of the initial model used annotated ECG signal recordings taken from the MIT-BIHARR[19]. The reason behind using the MIT-BIH-AR dataset is to fairly compare our proposed E-QRSM model with state-of-the-art methods. According to the ANSI/AAMI standards, four recordings (102,104,107, and 217) containing paced beats due to that signal does not retain sufficient signal quality for signal processing. The rest of the 44 recordings of MLII were taken for evaluation. It is essential to know that, the MIT-BIH arrhythmia dataset has five major classes of arrhythmia namely, non-ectopic beat (N), Supraventricular ectopic beat (S), Ventricular ectopic beat (V), Fusion beat (F), and Unclassified and paced beat (Q). The main focus of this study is to classify the V class; it includes ventricular ectopic beats (VEB). Therefore, only the V class was considered as abnormal beat and labeled as 1 for classifier training, and for the normal morphology structure, we consider Supraventricular ectopic beats (SVEB) which are labeled as 0.

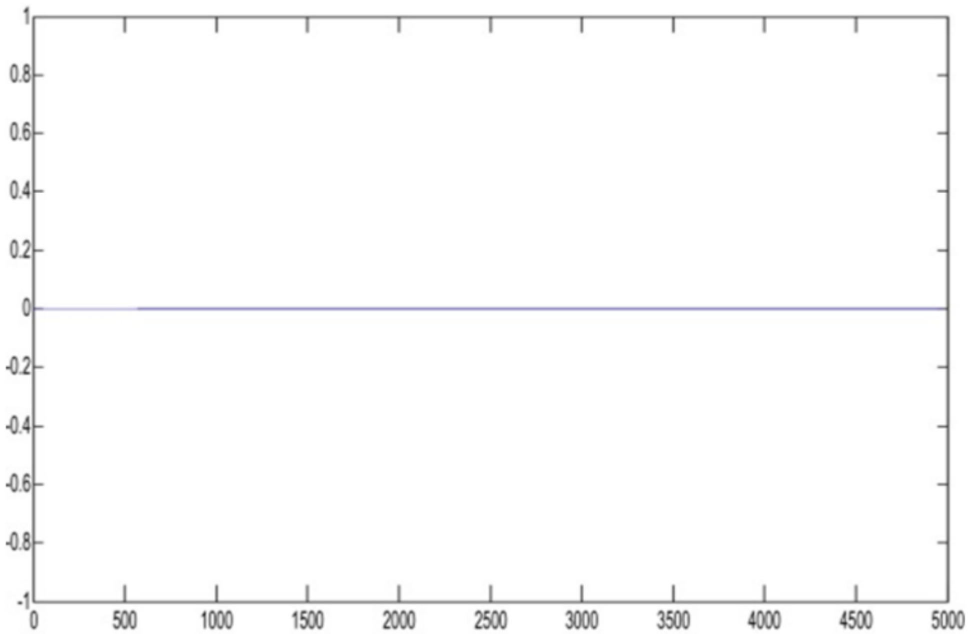

Figure 2. The representation of the leadoff signal.

4. E-QRSM METHODOLOGY

The following are the detailed steps of the E-QRSM methodology.

4.1. ECG Signal Pre-Processing

The raw ECG signal contains various types of noises and artifacts, due to that it cannot produce sufficient quality of ECG signal for further processing. This study follows three simple steps to produce noise-free signals.

1. To estimate the quality of ECG signals before proceeding toward the ventricular heartbeat classification is a quite challenging task. Sometimes wearable sensor device collects non-heart signals. The nature of those produced signals is to look like the straight signal without having any information of interest, these types of signals are called lead-off. It is necessary to discard that signal, otherwise, it will consider a large amount of noise in the signal. However, ECG signals contain different variations of amplitudes due to the onset and offset of the peak, if the amplitudes of the heat beats were constant in the ECG signal, then it is considered as lead-off signal. To determine the lead-off signals in our dataset we set the threshold value δ

= 1.5mV if the baseline drift occurs with a maximum value of amplitude than threshold mV it is considered as lead-off signal. The representation of lead-off signals is shown in Figure 2.

2. Re-scaling: This first stage aims to normalize the collected raw ECG signal to remove the DC offset from the signal amplitude by using this derived equation.

$$x_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Where:

- x= the sample of ECG signal
- i= index of consecutive signals samples
- min(x)= minimum signal amplitude
- max (x)=maximum signal amplitude

3. Signal filtration plays a vital role in producing a quality vector of ECG signals. The main reason for the application of filters in this research is to get valuable and precise results in the classification part as we mentioned above that, a biased diagnosis can lead to many health issues in patients. Therefore, to reduce the signal-noise ratio this research applied the notch filter and median filter for the removal of power line interference and baseline drift in the ECG signal respectively. In literature, many studies used these filters which have the same aim of classification [7],[8], we also used that technique to produce good results for our classification model. The filtered result of the ECG signal is depicted in Figure 3.

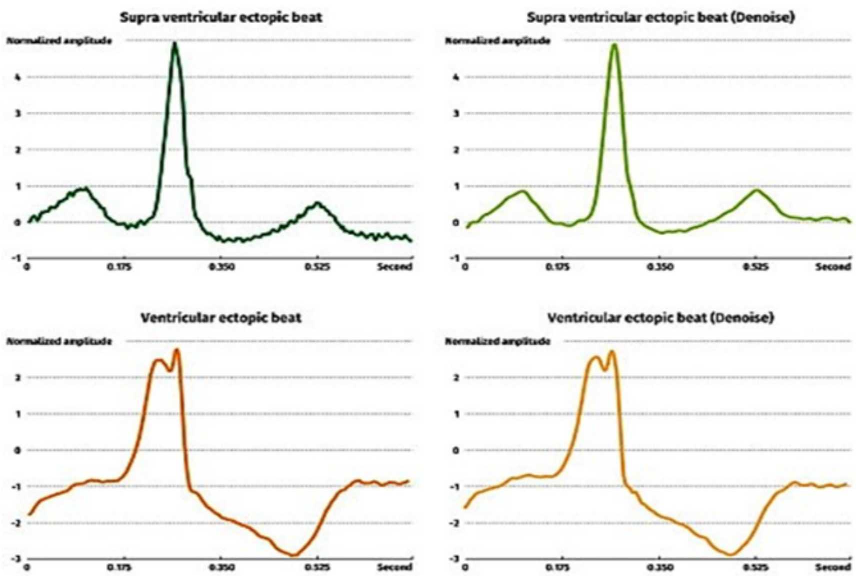

Figure 3. The graphical representation of the noisy signal and filtered signal.

4.2. ECG Heartbeat Detection and Segmentation

The main aim of this subsection was to detect the ECG heartbeat from the raw signal and segment the complete cycle for ventricular heartbeat classification. The main reason for the detection and segmentation of heartbeat was to separate the normal and abnormal beats because ventricular ectopic beats often exist between the normal beats. The main objective of heartbeat detection is to identify the prominent feature QRS complex of the ECG signals which helps to recognize the different patterns of the heartbeat. The first and foremost part of this section is to identify the QRS complex. This feature is the common attribute of ECG signal which helps to identify a regular and irregular heartbeat. To detect this common and most important feature, this study used the modified Pan and Tompkins algorithm which is widely used in many studies [20], [9] another reason for using this most common and famous algorithm in this study is that it adapts the signal changes very efficiently. The starting point and endpoint of the highlighted area are called Q and S points whereas the highest peak indicates the R point. Based on the detection of this primary feature, other major attributes related to the R point were extracted from each segment of ECG signals. To identify the other values in each segment of the heartbeat, a vector of ECG samples was divided into a fixed length of around 5 seconds which is represented as =5s. Subsequently, the complete cycle of ECG heartbeat is denoted as, and the R-peak was identified by the modified pan Tompkins algorithm which is denoted as

$$\boldsymbol{\partial}_{\boldsymbol{i}}= \{\boldsymbol{\partial_1},\boldsymbol{\partial_2},\boldsymbol{\partial_3},\boldsymbol{\partial_4},\ldots..\boldsymbol{\partial_n}\},$$

whereas RR intervals are highlighted as $|(\boldsymbol{\partial}+\mathbf{1})-(\boldsymbol{\partial})|$

and QRS complex is represented as $\alpha= \{\alpha_1, \alpha_2, \alpha_3 ,\alpha_4,\ldots\ldots, \alpha_n\}$.

Equation3, 4, and 5 represented the average values of the RR interval, the standard deviation of the RR interval, and several peaks respectively.

$$\boldsymbol{\mu RR} = \frac{\mathbf{1}}{\boldsymbol{\rho}}|(\boldsymbol{\partial}+\mathbf{1})-(\boldsymbol{\partial})| \tag{2}$$

$$\boldsymbol{SdevRR} = \sqrt{\frac{\mathbf{1}}{(\boldsymbol{\rho}-\mathbf{1})}\sum_{i=1}^{\varepsilon}[|(\boldsymbol{\partial}+\mathbf{1})-(\boldsymbol{\partial})|-\boldsymbol{\mu}]} \tag{3}$$

$$\boldsymbol{numpks} = \boldsymbol{length}(\boldsymbol{\alpha}) \leq \tau \tag{4}$$

In the final stage, when all points related to the QRS complex were extracted from the complete subject of ECG, we consider R-peak as the reference or location point which can be used for the further extraction of other relevant information from. The constant length of around 0.52s has been set for the searching mechanism of other relevant beats. The search starts from the left side and ends until 0.26s are reached and the rest of the 0.26s is consumed for the right side of the reference point. According to the medical practitioner's suggestion, the abnormal beat of ventricular origin is represented by a wider QRS complex and irregular RR intervals. To elaborate further, for clear identification of abnormal ventricular heartbeat Pearson's correlation coefficient (PCC) technique was used. The formula of the PCC feature is according to:

$$\boldsymbol{\beta} = \{\boldsymbol{\beta_1},\boldsymbol{\beta_2},\boldsymbol{\beta_3},\ldots,\boldsymbol{\beta_n}\}$$

$$\boldsymbol{cc_i} = \{\boldsymbol{c_1},\boldsymbol{c_2},\boldsymbol{c_3},\ldots\ldots,\boldsymbol{c_n}\} \tag{5}$$

$$\boldsymbol{c_n} = \frac{\sum_{k=1}^{k}\boldsymbol{\beta_k}}{||\boldsymbol{\beta}||_2.\boldsymbol{\beta_{k_2}}} \tag{6}$$

$$\boldsymbol{\mu_{cc}} = \frac{\mathbf{1}}{\boldsymbol{j_i}}\sum_{j=1}^{j_i}\boldsymbol{c_n} \tag{7}$$

$$\boldsymbol{dev_{cc}} = \frac{\mathbf{1}}{\sqrt{\boldsymbol{j_i}-\mathbf{1}}}||\boldsymbol{cc_i}-\boldsymbol{\mu_{cc}}||_2 \tag{8}$$

(9)

Where β represented as the series of QRS segments, and are correlation coefficients, is denoted as the mean and is the deviation of the ventricular heartbeat. Our suggested approach also extracts the R-peak's opposite polarity, which is useful for detecting various forms of arrhythmias from ECG data. Figures 3 and 4 show the area of the interested block and the results of two occurrences, respectively. Our proposed technique EQ-RSM uses a simpler threshold value to reliably identify the P- and T-peaks in the ECG signal, which helps to reduce computational complexity

4.3. Recurrent Neural Network

A recurrent neural network (RNN) is a form of artificial neural network that is used to analyze time series or sequential data. RNNs, as opposed to feedforward neural networks, which process input data in a single pass from input to output, contain a feedback loop that allows information to remain over time and be exchanged across temporal steps. The potential of an RNN to keep an internal state or memory allows it to capture dependencies and patterns in sequential input. This internal state is modified at each time step, taking both the current input and the prior state into consideration. RNNs may make predictions or create outputs that are impacted by the full input sequence by integrating information from prior time steps. A recurrent neural network (RNN) has various parameters that govern the network's behavior and properties. The critical RNN parameters are as follows: -Input Size: The dimensionality of the input at each time step is specified by this option. It determines the number of RNN input nodes. -The number of hidden nodes or memory cells in the RNN is determined by the hidden size. It indicates the dimensionality of the network's internal state or memory. -The output size specifies the dimensionality of the output at each time step. It determines the number of RNN output nodes. -The activation function is used to the RNN's input and hidden states to create nonlinearity and allow the network to learn complicated patterns. Sigmoid, tanh, and ReLU are examples of common activation functions. -Weight Matrix: Weight matrices manage the flow of information between the input, hidden, and output layers in RNNs. These matrices are learned throughout the training process and regulate how each layer affects the others. -The initial concealed state is the beginning point for the internal state of the RNN. It can be set to zeros or learned during training as a parameter. -Recurrent Weight Matrix: The recurrent weight matrix relates the previous time step's hidden state to the present time step's hidden state. It governs how the memory of the RNN is refreshed and transmitted over time. -Bias Terms: At each layer, bias terms are added to the weighted inputs to induce an offset or bias in the computation. They enable the RNN to learn various intercepts for various characteristics. To analyze the time-series data Recurrent neural network (RNN) is considered one of the best methods and it has many successful stories too for the ECG signal classification such as [10] ,[11] .

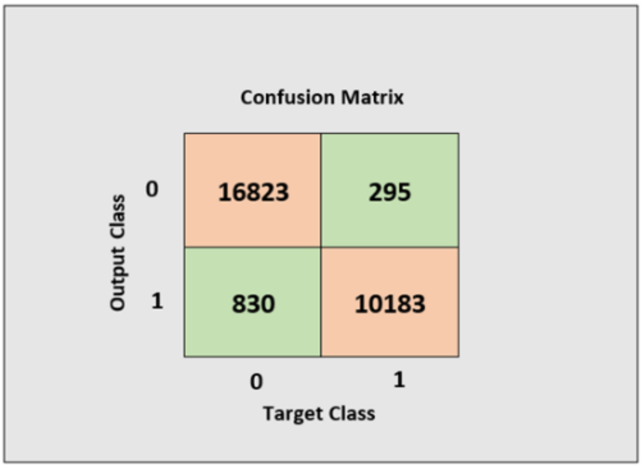

Figure 4. Confusion matrix of proposed E-QRSM Methodology

The architecture of the RNN method is used to process sequential time series data. It consists of three layers input layer, a hidden layer, and an output layer. RNN produces output according to each time step, the current output is not based on current input, but it is also related to the hidden state or previous step of the architecture. In the proposed study three layers of RNN are utilized for the classification of PVC arrhythmia, each layer includes 127,250 and 100 neurons respectively with 10 iterations. The dropout rate was constant adding 0.2 at each layer. Tunned RNN plays a very effective role in the classification instead of using the conventional method of RNN. The ReLU activation function was used with MSE as the loss function.

5. Results and Discussion

The performance was measured using three primary measuring performances on RNN models: accuracy, specificity, and classification sensitivity using the confusion matrix as shown in figure 5. For binary classification,

Accuracy = $\frac{(TP+TN)}{(TP+TN+FP+FN)}$.

Sensitivity = $\frac{TP}{(TP+FN)}$

Specificity = $\frac{TN}{(FP+TN)}$

Where

1. True Positives (TP): The number of cases accurately predicted as positive is (16823).
2. True Negatives (TN): The overall number of cases accurately predicted as negative is (10183).
3. False Positives (FP): The number of incidents that are wrongly forecasted as positive is (295)
4. False Negatives (FN): The number of instances that are incorrectly predicted as negative is (830)

The ratio of true positive beats has existed when arrhythmia was accurately detected and it identifies the performance of the algorithm and the ratio of true positive beats is higher than the rest of the others if the algorithm works efficiently. The classification accuracy represents the total number of beats that are properly classified as Normal or Arrhythmia. Furthermore, this study compares the proposed E-QRSM methodology with FCM [12]and FLM [13] models of feature extraction in which this study observed that our proposed methodology for E-QRSM achieved the best performance among the state-of-the-art models.

Table 1. Comparison of Proposed Study with State-of-the-art Methods

Studies	Accuracy	Sensitivity	Specificity

(Cuesta et al., 2014)	80.94%	90.13%	82.52%
(Talbi & Ravier, 2016)	95.00%	85.00%	95.00%
Proposed	96.00%	92.23%	97.18%

6. Limitation and Future work

The experimental analysis of this study only deals with public benchmark datasets. However, private datasets require immense preprocessing of the ECG signals. In future work, our aim is to consider the different types of arrhythmia detection using the proposed E-QRSM model in the federated learning system. So, we can use more data for training the classifier to improve the classification accuracy of the model. Classification accuracy can be improved by tuning the value of epochs and neurons in the hidden layer, it will be considered as a future work of this manuscript.

7. Conclusion

The RNN showed an accuracy of 96.0% when we take the number of iterations to be 5 and hidden layers to be 3 and there are 64, 256, and 100 neurons per hidden layer respectively which shows better detection of arrhythmia than the previous state-of-the-art methods. The detailed methodology is described in Figure 1 in which proper filtering technique has been employed for the pre-processing as this is the essential process in electrical analysis activity. It is observed throughout the process of designing the E-QRSM methodology that the algorithm that adapts the variation of the ECG signals is better and more accurate. Therefore, this methodology aims to adapt the variation and classify the PVC arrhythmia efficiently as this arrhythmia has a lot of variations. Our suggested approach detects negative peaks with ease. This methodology is useful for identifying several types of arrhythmias, including PVC arrhythmias. This methodology may be utilized to identify many forms of arrhythmias. We determined that our proposed fully automatic model outperformed existing state-of-the-art investigations.

References

1. C. Lv, Y. Xing, J. Zhang, X. Na, Y. Li, T. Liu, D. Cao, F.-Y. Wang, Levenberg–marquardt backpropagation training of multilayer neural networks for state estimation of a safety-critical cyber-physical system, IEEE Transactions on Industrial Informatics 14 (8) (2017) 3436–3446.
2. S. Chen, W. Hua, Z. Li, J. Li, X. Gao, Heartbeat classification using projected and dynamic features of ecg signal, Biomedical Signal Processing and Control 31 (2017) 165–173.
3. M. K. Gautam, V. K. Giri, A neural network approach and wavelet analysis for ecg classification, in: 2016 IEEE international conference on engineering and technology (ICETECH), IEEE, 2016, pp. 1136–1141.
4. O. Castillo, P. Melin, E. Ram´ırez, J. Soria, Hybrid intelligent system for cardiac arrhythmia classification with fuzzy k-nearest neighbors and neural networks combined with a fuzzy system, Expert Systems with Applications 39 (3) (2012) 2947–2955.
5. Z. Dokur, T. Olmez, Heartbeat classification by using a convolutional neural network trained with walsh func- ¨ tions, Neural Computing and Applications 32 (16) (2020) 12515–12534.
6. S. L. Oh, E. Y. Ng, R. San Tan, U. R. Acharya, Automated diagnosis of arrhythmia using combination of cnn and lstm techniques with variable length heart beats, Computers in biology and medicine 102 (2018) 278–287.
7. U. Iqbal, T. Y. Wah, J. H. Shah, et al., Prediction analytics of myocardial infarction through model-driven deep deterministic learning, Neural Computing and Applications 32 (20) (2020) 15909–15928.
8. Q.-U.-A. Mastoi, T. Y. Wah, R. Gopal Raj, Reservoir computing based echo state networks for ventricular heart beat classification, Applied Sciences 9 (4) (2019) 702.
9. L. Sathyapriya, L. Murali, T. Manigandan, Analysis and detection r-peak detection using modified pan-tompkins algorithm, in: 2014 IEEE International Conference on Advanced Communications, Control and Computing Technologies, IEEE, 2014, pp. 483–487.
10. S. Savalia, V. Emamian, Cardiac arrhythmia classification by multi-layer perceptron and convolution neural networks, Bioengineering 5 (2) (2018) 35.
11. M. Limam, F. Precioso, Atrial fibrillation detection and ecg classification based on convolutional recurrent neural network, in: 2017 Computing in Cardiology (CinC), IEEE, 2017, pp. 1–4.
12. P. Cuesta, M. J. Lado, X. A. Vila, R. Alonso, Detection of premature ventricular contractions using the rrinterval signal: a simple algorithm for mobile devices, Technology and Health Care 22 (4) (2014) 651–656.
13. M. L. Talbi, P. Ravier, Detection of pvc in ecg signals using fractional linear prediction, Biomedical Signal Processing and Control 23 (2016) 42–51.
14. Mastoi, Qurat-ul-ain, Novel derma fusion technique for ecg heartbeat classification, Life 31 (2022) 842.
15. Shaikh, Asadullah, S. AlYami, A fully automatic model for premature ventricular heartbeat arrhythmia classification using the internet of medical things., Biomedical Signal Processing and Control 31 (2023) 83.
16. Kumar, Ashwani, K. Mohiuddin., Flamingo-optimization-based deep convolutional neural network for iot-based arrhythmia classification., Sensors 9 (2023) 4353.
17. Wang, Yue, D. Liu., Arrhythmia classification algorithm based on multi-head self-attention mechanism., Biomedical Signal Processing and Control 9 (2023) 79.
18. Xiao, Qiao, P. Y. Lim.., Deep learning-based ecg arrhythmia classification: A systematic review., Applied Sciences 8 (2023) 4964.
19. R. Mark, G. Moody, Mit-bih arrhythmia database directory, massachusette inst, Technol.(MIT).
20. S. Gradl, P. Kugler, C. Lohm¨uller, B. Eskofier, Real-time ecg monitoring and arrhythmia detection using android-based mobile devices, in: 2012 annual international conference of the IEEE engineering in medicine and biology society, IEEE, 2012, pp. 2452–2455