Preparing the Electrical Signal Data of the Heart by Performing Segmentation Based on the Neural Network U-Net

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***Abstract* – Research on the automated extraction of essential data from an electrocardiography (ECG) recording has been a significant topic for a long time. The main focus of digital processing processes is to measure fiducial points that determine the beginning and end of the P, QRS, and T waves based on their waveform properties. The presence of unavoidable noise during ECG data collection and inherent physiological differences among individuals make it challenging to accurately identify these reference points, resulting in suboptimal performance. This is done through several primary stages that rely on the idea of preliminary processing of the ECG electrical signal through a set of steps (preparing raw data and converting them into files that are read and then processed by removing empty data and unifying the width of the signal at a length of 250 in order to remove noise accurately, and then performing the process of identifying the QRS in the first place and P-T implicitly, and then the task stage is determining the required peak and making a cut based on it. The U-Net pre-trained model is used for deep learning. It takes an ECG signal with a customisable sampling rate as input and generates a list of the beginning and ending points of P and T waves, as well as QRS complexes, as output.**

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The distinguishing features of our segmentation method are its high speed, minimal parameter requirements, and strong generalization capabilities, which are used to create data that can be used in diagnosing diseases or biometric systems.

***Keywords* – Electrocardiography, signal, noise, extracting, QRS, peak, U-Net.**

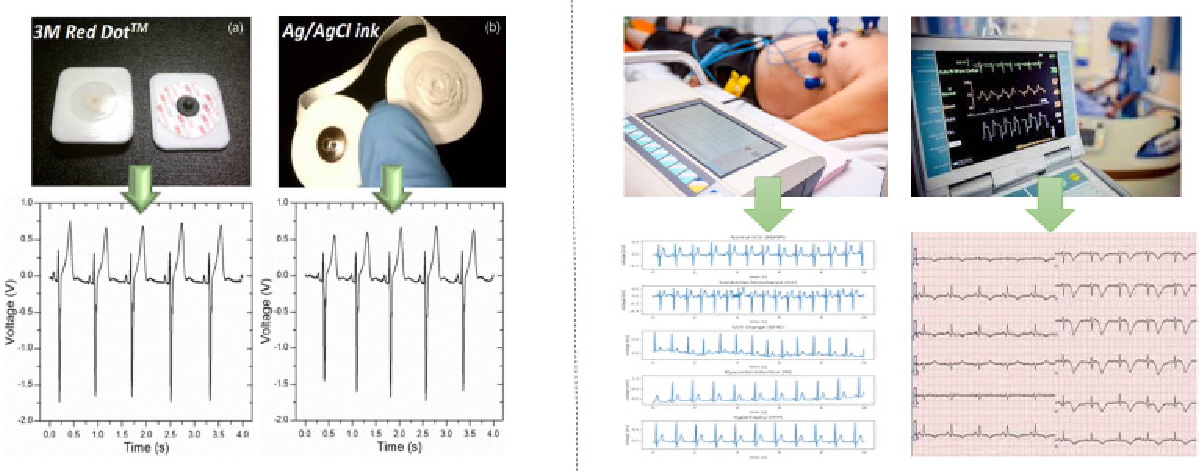
1. Introduction

An electrocardiogram (ECG) records heart electrical activity. These recordings are made with body electrodes [1]. Since biometric systems use this ECG to identify persons, it is considered a vital diagnostic tool for heart issues and disease. Modern research uses biometric methods to identify people. Researchers have been interested in automatic electrocardiogram (ECG) signal processing and have applied their findings to medical and security [2]. ECG analysis examines QRS complex P and T waves, including their forms, sizes, relative locations, and other properties. When segmenting or identifying an ECG signal, finding the start and end points of QRS complexes and P and T waves is crucial since it reduces data input and dependence on sections of the ECG, like clinicians do when reading a paper ECG [3]. Due to many reasons, automating reliable ECG segmentation is difficult. Electrode and muscle activity can obscure the P wave, which is low in magnitude [4]. The biphasic structure of P and T waves makes onsets and offsets difficult to determine. Abnormal cardiac cycles may lack a P wave. QRS complex identification was assessed on ECG [5]. From a medical perspective, the P wave, QRS complex, and T wave are the fundamental elements of the ECG signal. The provided data encompasses the measurements of the PR and QT intervals, together with the PR and ST segments [6]. Nevertheless, the process of identifying and distinguishing ECG segments becomes complex due to the diverse physiology of the reference sites, largely resulting from cardiac diseases [7].

These problems must be handled. The isoelectric line represents the baseline of the ECG signal, signifying the lack of electrical activity in the heart. Noise may cause interference or distortion in the ECG signal [8]. The process of segmenting an electrocardiogram (ECG) signal involves identifying the specific waves, segments, and intervals within the signal and then comparing them to established patterns based on their temporal and formal properties [9]. Also, the second purpose lies in scientifically preparing data and cutting it without loss to enter it into the neural network and prepare the data, whether for a medical or biometric system [10]. In this research paper, the importance of the signal segmentation process is highlighted, and a method with a new idea is proposed with a short segmentation time based on deep learning in order to prepare the data, whether for a medical situation or the subject of biometric systems so that the problem of the entrance to the neural network that is limited to one size is solved.

2. ECG Domain

The heart comprises specialised cells with inherent excitability, which generate electrical impulses that initiate the mechanical contraction of the muscle fibres [11]. An electrocardiogram (ECG) measures one's electrical activity over time. An electrocardiogram (ECG) is typically obtained using an array of electrical leads on the chest [12]. The process of placing electrodes on the human chest is not quite practical from the point of view of biometrics due to the mechanism of their installation and placement of people, and as a result other methods have recently been introduced, such as the method in which a single-lead setup is proposed to obtain an ECG signal at the fingers using Ag/Ag electrodes. AgCl without gel or through a smart watch or all of these modern and advanced methods that rely on the idea of small-sized devices that are efficient in output [13]. Therefore, the ECG has many aspects, including medical, biometric, and research aspects for evaluating algorithms, all of which lead to a basic idea: preparing the data before using the algorithm [14]. Figure 1 illustrates the different devices that can obtain the signal from humans where (a) ECG biometric and can used to classify diseases if diagnosed by doctor, (b) for heart diseases diagnosis and biometric (evolution the algorithm).



(A) ECG signal at the fingers using Ag/AgCl

(B) ECG signal From 12-lead device

Figure 1. ECG signal model

The electrical signal of the heart is shown in Figure 2. with the best feature that can be obtained from one signal.

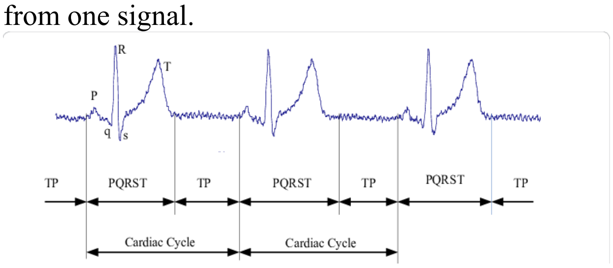


Figure 2. Electrical signal of the heart[15]

Electrocardiograms measure the potential difference between two locations and define electrocardiogram (ECG) traces as a visual depiction of electrical potential difference changes. Each wave in an electrocardiogram (ECG) trace represents a phase of the heart's electrical cycle. The P, Q, R, S, and T waveforms are characteristic of electrocardiogram (ECG) tracings. P waves indicate the observed electrical activity in the atria of the heart [16]. The QRS complex signifies the electrical activity occurring in the ventricles, which are the lowest chambers of the heart.

Ventricular repolarization is shown by the T wave. The PR interval represents the duration between the P wave and the QRS complex, indicating the time required for the electrical impulse to propagate from the atria to the ventricles. The QT interval is defined as the duration between the QRS complex and the T wave. The QT interval is the time needed for the ventricle to undergo contraction and repolarization. At this step, the use of a specific filter is intended to improve the quality of the signal by reducing distortion and limiting the loss of important information [17].

3. ECG Segmentation

Accurate automated detection of fiducial points in an electrocardiogram (ECG) is crucial for the automated analysis of this captured electrical signal. There are several well-established techniques in the literature to segment ECG data automatically and manually, and it is considered one of the complicated topics in the signal processing part [18]. These algorithms rely on distinct methods and are frequently evaluated using diverse datasets and protocols, which complicates the task of evaluating their performance due to the difficulty of the data available to researchers [19]. Segmenting an electrocardiogram (ECG) automatically is a huge challenge for researchers due to many ideas, but the basis must be purely medical according to the standards recommended by doctors. Because medical devices have different versions and different generations play an essential role, this phenomenon can be explained through various forms. Which appear in the QRS complex, decreased P wave size, and smooth transitions that occur at the beginning and end of the T wave [20]. Furthermore, the lack of a universally acknowledged criterion for accurately establishing the exact positioning of fiducial points adds an extra level of intricacy to this undertaking [21]. There are several techniques documented in the scientific literature that can be used to automatically segment ECG data into segments. The majority of solutions focus on defining a restricted set of fiducial points within an electrocardiogram (ECG). Implementing a standardized approach to identify all fiducial sites may present difficulties due to the distinct features of ECG waves, including their shape, frequency, magnitude, and duration [22]. In Figure 3 an example of a signal peak that can be segmented based on the feature can be shown.

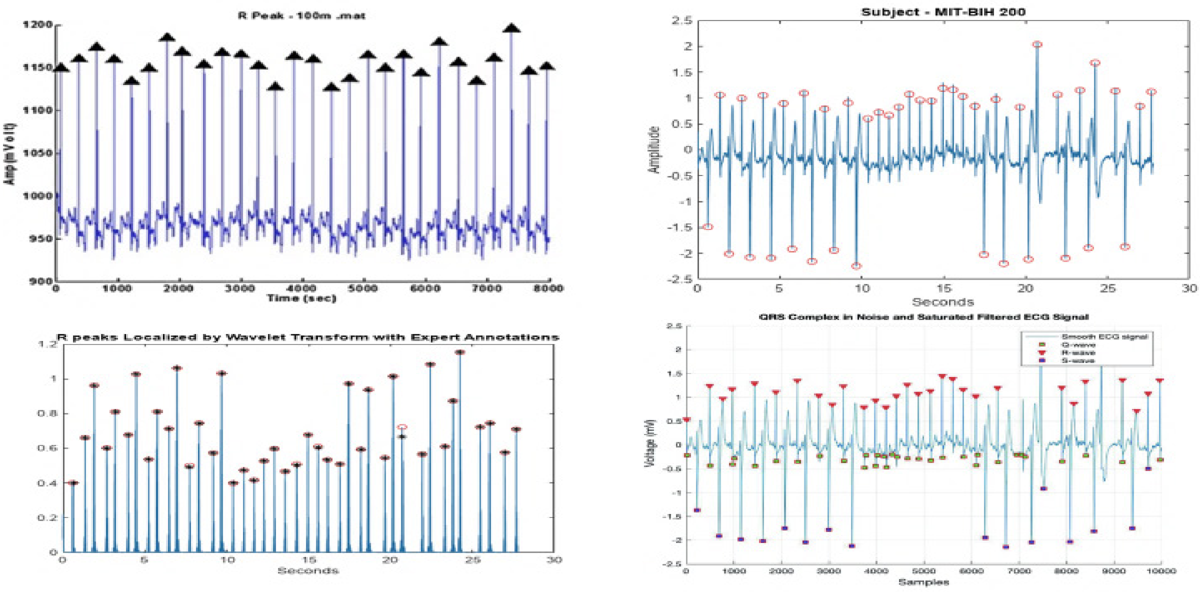


Figure 3. Peak example of signal

4. Related work

There are many studies on ECG signal segmentation; the following studies are related to segmentation based on the same dataset.

Study [23] contains a core paper for a dataset (Lobachevsky University Database (LUDB)) that proposed steps in ECG signal segmentation, A comprehensive tool for verifying ECG delineation approaches that exceeds the capabilities of existing public datasets in some ways. The LUDB dataset comprises two hundred 10-second 12-lead electrocardiogram (ECG) recordings acquired from various sources. These topics in the dataset show a variety of signal shapes. For each recording, cardiologists annotate the boundaries and pinnacles of QRS complexes, P waves, and T waves by hand. Each individual lead is annotated. Furthermore, every record is thoroughly categorised to identify any anomalies. The present case study examines the integration of the widely used ecg-kit application with the recently developed wavelet-based approach.

The purpose of this paper is to illustrate the benefits of analysing multi-lead ECG data. LUDB broadens the assortment of publicly accessible datasets that are utilised in the development and validation of sophisticated electrocardiogram (ECG) analysis techniques, encompassing cutting-edge approaches that rely on deep-learning neural networks. Studies suggest that delineation tools may exhibit variations in performance when used to diverse datasets. The probable cause for the many instrumental origins of ECG is its limited size. The divergence in expert viewpoints about demarcation and identification may have a substantial impact on the verification and practical application. Nevertheless, there is a lack of evidence available to evaluate and resolve this matter. Moving forward, the primary focus of quality assurance for demarcation algorithms will transition from attaining optimal performance for a specific case to guaranteeing consistent and dependable performance across numerous datasets. Authors of study [24] suggest an approach for segmenting electrocardiogram (ECG) signals into sections using a fully convolutional neural network, akin to UNet. The programme accepts an ECG signal with a fluctuating sampling rate as input and produces a list of the starting and ending positions of P and T waves, as well as QRS complexes, as output. Our segmentation approach stands out for its rapidity, minimal parameter count, and strong generalisation capabilities. This device possesses the capability to adapt to different sampling rates and is compatible with a diverse range of ECG monitors. The proposed technique surpasses previous state-of-the-art segmentation algorithms in terms of quality. Study [25] presents a new method for precisely locating the QRS complex and T wave in multi-lead ECG data. This technique uses a U-Net framework with convolutional neural networks, long short-term memory, and ensemble learning. The model used a multi-lead ECG to extract robust temporal correlation and exact morphological features during training. The model assigned likelihood scores to each data point. Dynamic threshold adaptive adjustment was used to identify QRS complexes and T waves during decision-making. Electrophysiological knowledge (EK) was used to assess and aggregate lead data, minimising missed and inaccurate detections.

The deep learning and EK approach was verified using three open databases. Experimental results showed that the proposed method outperformed state-of-the-art methods. The precise localization of specific spots in wearable ECG readings constituted a hurdle in the proposed system, primarily due to significant noise levels [12]. We developed the ECG_SCRNet, a site regression network that incorporates sequential constraints to accurately detect the distinctive spots of the wearable ECG, considering both the temporal sequence of waveforms and any missing waveforms. A classification header has been included to ascertain the presence of a missing P wave or T wave. This architectural design integrates the chronological order of events, the patterns of human behaviour, and the geological knowledge to improve the accuracy of identifying significant locations in the network. The performance of the ECG_SCRNet model was evaluated using the LUDB dataset. Deep learning surpasses traditional algorithms in supervised tasks when there is a substantial quantity of training data accessible. Accurately identifying P, QRS, and T waves presents a difficulty in the interpretation of ECG waveforms. This paper introduces an innovative method that combines deep learning and sequential constraint regression to precisely identify the position of three waveforms. After undergoing training, the system effectively identified the locations of waves by integrating waveform categorization with forecasts of the initial and final points.

5. Proposed System

The electrical signal to the heart is an essential topic for researchers, especially how to segment the signal. In this approach, a model dedicated to segmentation is proposed, but in a way that has a similar idea by performing processing operations to format the data, whether it is used in biometric systems, in diagnosing heart disease, or in testing the efficiency of the algorithm, where the basic idea is to determine the number of QRS pulses in a basic form and P-T in a basic form. Second, the desired number is chosen and then chopped based on deep learning. Figure 4 displays the suggested framework of the approach.

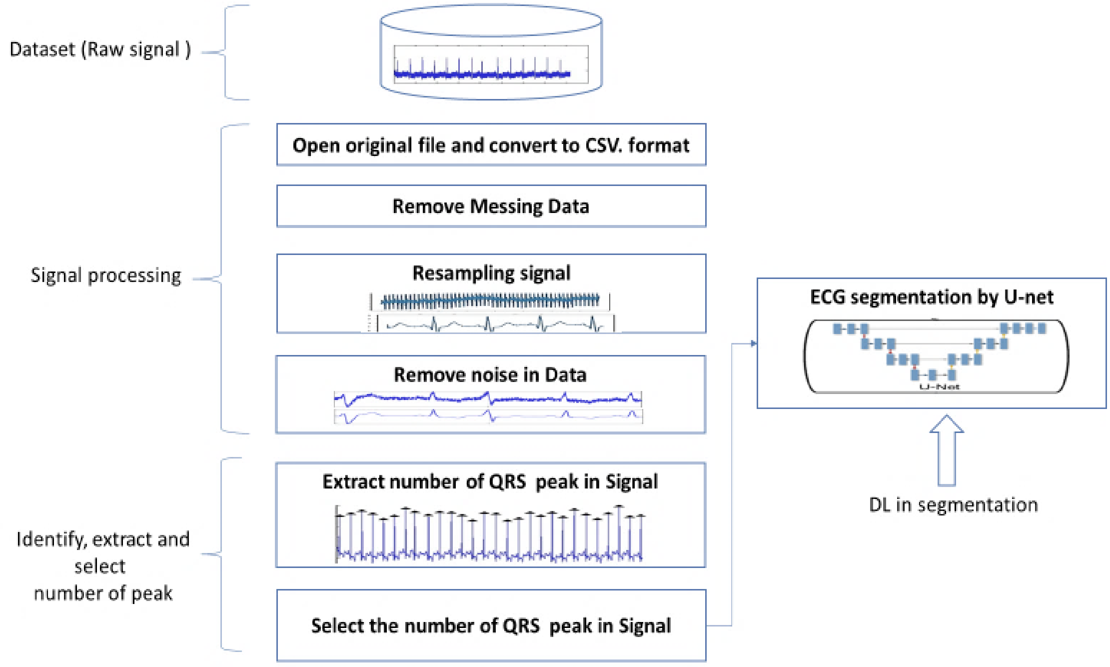


Figure 4. proposed outline of the approach

5.1. Dataset Used

The database for electrocardiography at Lobachevsky University (LUDB) [23] includes electrocardiogram (ECG) data exhibiting distinct and well-defined boundaries and peaks for the P, T, and QRS complexes. The collection contains 200 10-second 12-lead ECG signal recordings, each displaying distinct morphologies. In the years 2017-2018, Healthy People collaborated with Nizhny Novgorod City Hospital No. There were 5 patients who submitted electrocardiograms (ECGs). Several individuals exhibited pacemakers and other cardiovascular conditions. Cardiologists carefully marked all 200 data for P, T, and QRS complexes. Each record corresponds to a diagnosis. The database has the capability to instruct and assess ECG delineation methods for educational purposes. This entails the automated identification of the borders and peaks of P, T, and QRS complexes. Accurate and detailed databases including complicated and wave data are required to verify the accuracy of ECG delineation methods. The collections that are now accessible are the MIT-BIH Arrhythmia Database, European ST-T Database, and QT Database. Please note that their annotation is not fully comprehensive. The MIT-BIH Arrhythmia Database and European ST-T Database annotate QRS complexes.

While a significant number of complexes lack labels, the QT database has annotations specifically for P, QRS, and T waves. The objective behind the development of the Lobachevsky University (LUDB) electrocardiogram (ECG) database was to rectify these issues (Figure 5).

The frequency at which articles utilised the given dataset from 2021 to 2023 is denoted.

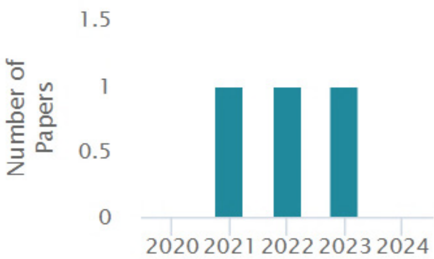


Figure 5. The LUDB dataset was used by the researcher

The database comprises 200 ECG signal records lasting 10 seconds and 12 leads. These records were gathered between 2017 and 2018. The total number of annotated waves is 58,429, which consists of 16,797 P waves, 21,966 QRS complexes, and 19,666 T waves. The age of the participants spanned from 11 to over 89 years, with a mean age of 52. The gender breakdown consisted of 85 women and 115 males. Table 1 summarises the details of the dataset used.

Table 1. number of records with specified heart rate types in the dataset

Rhythms	Number of ECGs
Sinus rhythm	143
Sinus tachycardia	4
Sinus bradycardia	25
Sinus arrhythmia	8
Irregular sinus rhythm 2	null
Abnormal rhythm	19

Based on Table 1, note that the data is collected excellently, as it contains many cases, which helps detect and determine QRS due to the different types of signals.

5.2. Signal Processing

In order to deal with data of this type, the files are converted from the folder in which they are located to files with a CSV extension. This step is essential to prepare the data, as after the conversion, the empty fields that indicate an electrical signal for a person but do not contain information are eliminated. This is a step (remove messing data), which was referred to in the table, represents the (irregular sinus rhythm 2) data, which was empty. Thus, move to a critical stage, the work of (resampling the signal), where the idea or benefit is to slow down the signal for a more transparent review of the pulses. Peak, where this percentage (250) was adopted based on experience for all 12 leads, as it was chosen as an intermediary between them because the goal is to work on all leads and the original percentage (250), and Figures (6,7,8, and 9) show the difference between the original signal and the signal that was resampled.

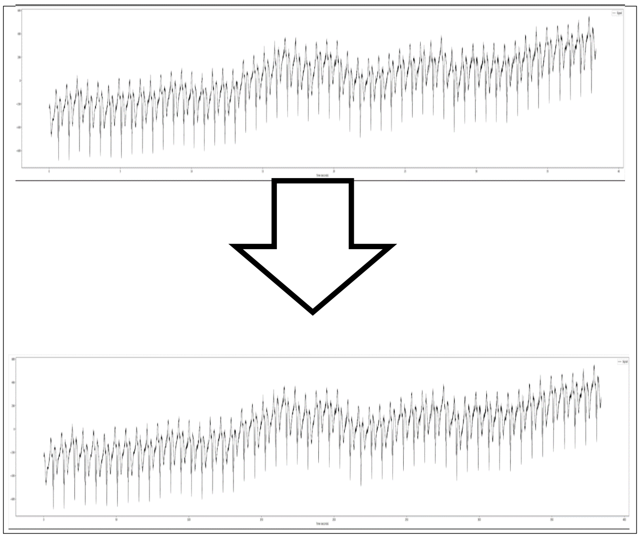


Figure 6. Before and after signal resampling (example one)

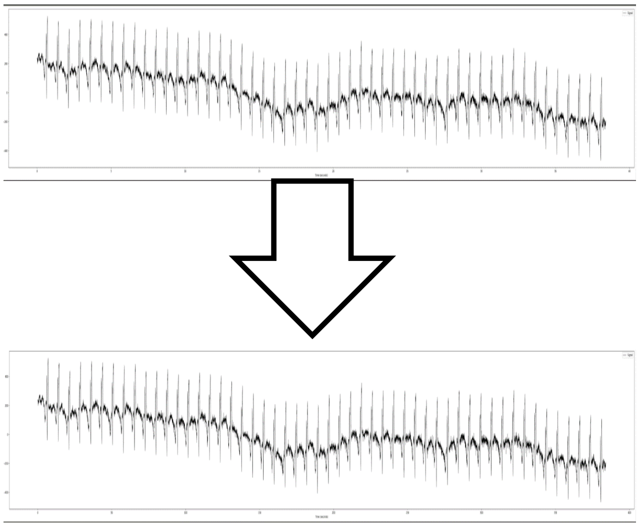


Figure 7. Before and after signal resampling (example two)

Based on the figures above, resampling an ECG signal involves altering the sampling rate, which refers to the frequency at which the signal is sampled per unit of time. The proposed approach ensures signal compatibility with segmentation by enhancing peak number clarity. This can be achieved for several reasons: to minimize the data that needs to be stored or transmitted. Resampling the ECG signals at a lower frequency can effectively minimize the size of the enormous data files used in the suggested approach. This is particularly significant for applications with constraints on storage capacity or bandwidth. In order to enhance the precision of ECG analysis methods utilized for QRS detection, it is advantageous to employ signals with a specific sampling rate. This step is done by using sample code in Python (resampled_ecg = signal.resample(ecg_signal, num). The last step in the ECG signal's processing stage is removing the noise in the signal, as the following figure shows the difference between before and after removal.

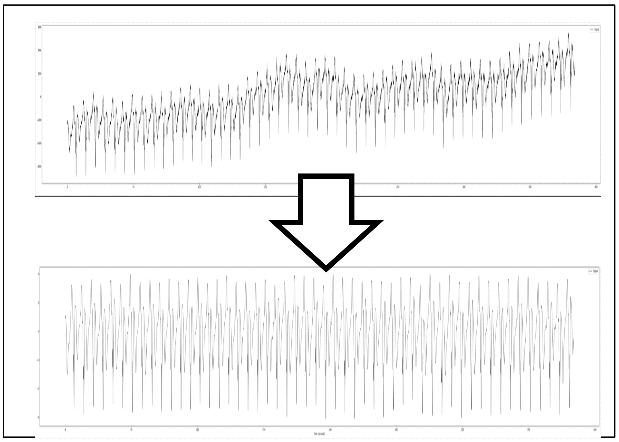


Figure 8. Before and after removing noise in signal ECG with normalization (example one)

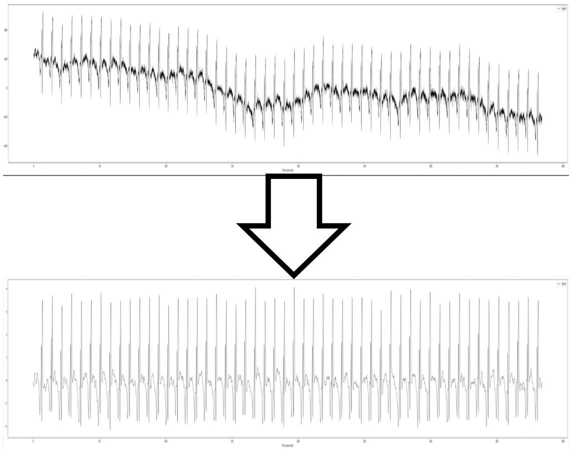


Figure 9. Before and after removing noise in signal ECG with normalization (example Two)

The proposed approach concluded that the LUDB data set of ECG signals contains different types of noise and is therefore considered one of the data sets that represent a challenge for researchers. The following is a breakdown of the prevailing types of noise:

- Baseline wandering: This slow, low-frequency drift of the baseline can be caused by breathing, electrode movement, and body position changes.
- Power line interference: This 50/60 Hz buzz originates from electrical equipment and can be picked up by ECG electrodes.
- Muscle artefact: This high-frequency noise arises from muscle contraction and can obscure basic ECG features such as QRS complexes.
- Electrode artefact: This noise is caused by poor electrode contact, movement, or sweating and can appear as sharp spikes or base shifts.
- Electromagnetic interference (EMI): This noise can be generated by nearby electronic devices and can appear as random spikes or bursts of high-frequency activity.

The suggested technique clearly demonstrates the impact of noise, namely muscle artefact, on the signal, as seen in the aforementioned pictures (examples one and two). A high-pass filter was employed to eliminate the noise that influenced the peak determination. This filter operates by allowing lower-frequency signals to pass through while blocking any frequencies above a specified threshold, typically set at 150 Hz. This threshold is chosen because the clinically significant information in the ECG is found below this frequency.

Nevertheless, if there is noise present in the electrocardiogram (ECG) frequency range that originates from muscle interference or the surrounding environment, it is possible to adjust the cutoff frequency to reduce its impact. This procedure was performed on a 12-lead dataset and successfully processed the data to enable the detection, identification, and selection of the number of peaks to be segmented.

5.3. Extraction and Selection of the Number of Peaks

The proposed approach used three main functions to find (QRS-T-R) and is summarized in Table 2.

Table 2. Primary function to find (QRS-T-R) in the proposed approach

(ecg_delineate())	This system is specifically designed to identify and analyse peaks in order to accurately define the QRS complex, which represents the many waves of the heart's cycles. An ordinary electrocardiogram (ECG) heartbeat comprises a P wave, a QRS complex, and a T wave. The P wave signifies the propagation of depolarization from the SA-node across the atria. The QRS complex represents the rapid depolarization of both the right and left ventricles. Due to the ventricles being the heart's greatest component in terms of mass, the amplitude of the QRS complex is often much greater than that of the P-wave. The T wave signifies the process of ventricular repolarization in the heart's ventricles. At times, a U wave may be seen subsequent to the T wave. The U wave is thought to be associated with the latter stages of ventricular repolarization.
ecg_findpeaks())	This is the underlying function used by ecg_peaks() to detect R-peaks in an ECG signal using various techniques. Utilise the main function and refer to its documentation for specific information.
(ecg_peaks())	Detect T-peaks in an electrocardiogram (ECG) signal with the designated methodology.

5.4. ECG Segmentation by U-Net (Neural Network Architecture)

The neural network design of the suggested technique has resemblance to that of U-Net. A single lead's electrocardiogram (ECG) signal length, represented as (l), serves as the neural network's vector input. The neural network is supplied with each lead independently. The output is four litres. The neural network's confidence in classifying the current signal value as belonging to segments P, QRS, T, or none of them is represented by the four scores that each column of the output matrix contains. The layers that make up the neural network being discussed are: (i): Each of the four blocks comprises two convolutional layers that are normalised in batches and employ the ReLU activation function. The units are sequentially coupled through the utilisation of MaxPooling layers; (ii) The output from the preceding layer is sent via a MaxPooling layer and used as input before another block that consists of two convolutional layers with batch normalisation and the Rectified Linear Unit (ReLU) activation function; (iii) The merging of pre- and post-layer outputs is accomplished by means of deconvolution and zero padding layers. Then, a block with two convolutional layers that use batch normalisation and the ReLU activation function takes the output as input. This follows a series of deconvolution and zero padding layers applied to the prior layer's output. Each of the four blocks takes the previously specified output and uses it to train two convolutional layers using batch normalisation and the Relu activation function. At each level, the output is combined with the output from the corresponding layers in reverse order. The last step is to forward the output of one convolutional layer to the next. With the kernel size set to nine, each convolutional layer receives a four-padding. The kernel size, stride, and padding are set to 8, 2, and 3 for each deconvolution layer, respectively. The kernel size for the last convolutional layer is defined as 1. Plainly understood the suggested network differs significantly from the traditional UNet design in that it uses 1D convolutions instead of 2D ones. The rationale for this decision was that the input data was imported from a CSV file, which led to a one-dimensional reduction in the matrix. Figure 10 illustrates the neural network architecture implemented in the proposed methodologies.

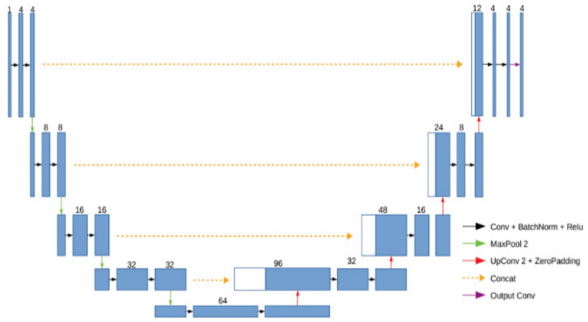


Figure 10. Neural network architecture in proposed approaches

Table 3 summarises the layer used in the proposed approaches.

Table 3. Summarized the layer used in the proposed approaches

Layer	**Description**
Conv	Convolutional layer. A convolutional layer serves as the primary building block of a convolutional neural network (CNN). The system comprises a set of filters (kernels) that will have their configurations learned throughout the training process.
Batchnorm	Batch normalisation, sometimes referred to as batch norm, improves the efficiency and robustness of training artificial neural networks. This is accomplished by standardising the inputs of the layers in the network via the processes of re-centering and re-scaling.
relu	ReLU is an acronym for rectified linear activation unit and is regarded as a significant breakthrough in the deep learning revolution. The activation function is simple and superior to previous alternatives like sigmoid or tanh.
Max pool	The max pooling layer is an essential convolutional neural network architecture element. It aids in extracting significant features from the input while lowering the data's dimensions.
Zero padding	The convolution process is executed on the input feature map that has been padded. Zero-padding is the most often used padding technique, where zeros are added to the edges of the input feature map. This technique can enhance the model's performance by mitigating information loss at the boundaries of the input feature map.

The following Figures illustrate the results of these three functions that can work to extract and select the number of peaks and segmentation signals.

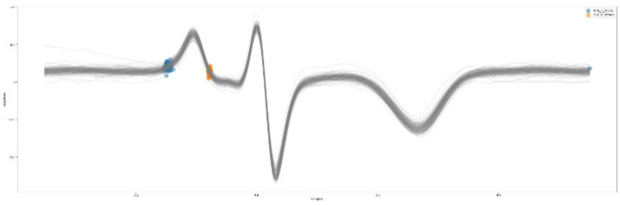


Figure 11. Detection and segmentation (P)

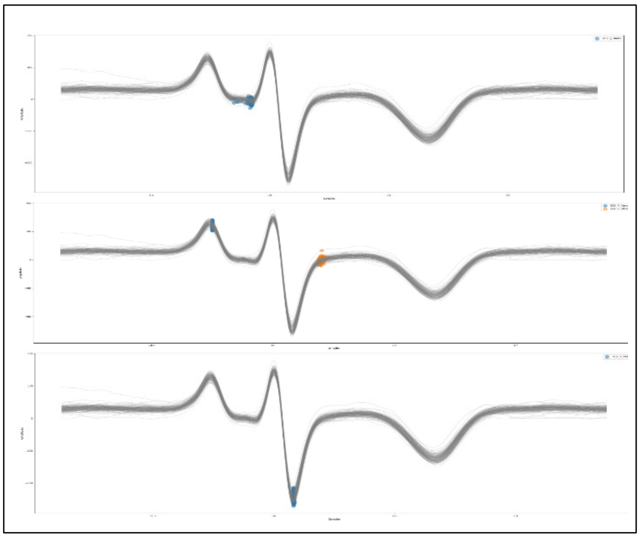


Figure 12. Detection and segmentation (Q-R-S)

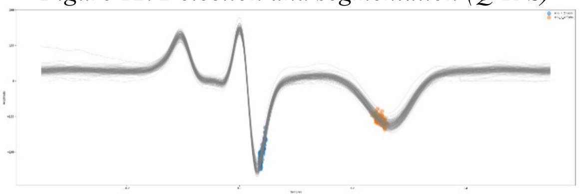


Figure 13: Detection and segmentation (T)

Based on the figures above, notice that the process of detection and segmentation was presented in a manner different from the research,

- → Figure 13: Represented the detection and segmentation of the (P wave), where the blue points represent the (P-offset) measure, the orange points represent the (P-onset), and the points are combined because they represent more than one signal that was taken.
- → Figure 14: The first signal represents the q wave, meaning the blue dots represent (Q (peak) in the ECG. The second signal represents the blue dots (R-onset), the orange dots represent (R-offset), and the last signal in Figure 14 represents the (s wave), where the blue dots represent the peak wave (s). The points are combined because they represent more than one signal that was taken.
- → Figure 15: Represented T wave, where the group of blue points will represent offset-T and the group of orange points will represent onset-T. This is the final stage through which the signal is segmented after the waves are identified as explained. Here the idea is that by identifying and detecting all these waves there is a more accurate segmentation. This step is the output of data that is processed, prepared, and segmented by a neural network U-NET that leads to outputs that can be entered. To the neural network without loss due to its large size. The points are combined because they represent more than one signal that was taken.
- →

6. Evolution the Results

The assessment of algorithm quality is conducted in accordance with the approach outlined by the Association for Medical Instrumentation guidelines. Accuracy in onset or offset detection is determined by whether the deviation of the detected values from the doctor annotations does not exceed a tolerance of 150 ms in absolute magnitude. A true positive (TP) outcome occurs when an algorithm accurately detects an important point, such as the beginning or end of one of the P, QRS, or T segments. The algorithm calculates the time difference (error) between the automatically detected position and the manually given spot. An I-type error, also known as a false positive (FP), occurs when there is no statistically significant point within the tolerance range of the identified significant point in the test sample. When the algorithm is unable to detect a significant point, it constitutes an error of type II, more precisely a false negative (FN). The subsequent quality indicators [26]:

- → The average error is denoted as "m".
- → The standard deviation σ represents the variability of the mean error.
- → Recall.
- → recall= TP/(TP + FN).
- → (TP + FP) divided by positive predictive value (PPV) equals precision (PP). The total number of correct solutions classified as type I and type II errors are denoted as TP, FP, and FN, respectively.
- → F1-measure: F1 = 2 Se · PPV Se + PPV

Table 4 below illustrates the result of 12-lead in proposed approaches.

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Table 4. Result of 12-lead in proposed approaches

No.lead	Scale	P onset	P offset	QRS onset	QRS offset	T onset	T offset
lead I	RE (%) PPV (%) F1 (%)	97.38 95.53 96.47	97.38 95.53 96.47	97.38 95.53 96.47	97.38 95.53 96.47	97.38 95.53 96.47	97.38 95.53 96.47
Lead II	RE (%) PPV (%) F1 (%)	93.66 94.56 93.30	93.80 92.66 92.88	96.90 97.99 97.98	98.99 96.80 95.97	96.22 94.44 96.49	92.23 92.56 93.65
Lead III	RE (%) PPV (%) F1 (%)	96.66 97.77 94.88	93.38 94.43 94.67	91.68 95.83 96.97	97.98 99.93 99.97	99.88 97.83 98.87	94.78 95.63 97.57
Lead aVF	RE (%) PPV (%) F1 (%)	94.28 96.33 95.47	94.48 95.43 97.57	97.68 94.73 95.77	98.98 98.93 98.97	99.78 99.73 99.77	98.18 98.13 91.17
Lead aVR	RE (%) PPV (%) F1 (%)	91.48 94.43 92.87	95.18 96.23 97.27	92.28 93.53 94.57	97.58 95.53 91.55	89.22 91.33 92.43	91.99 92.91 91.65
Lead aVL	RE (%) PPV (%) F1 (%)	95.77 98.59 95.49	97.58 96.53 99.97	97.98 99.93 99.97	94.14 91.15 96.20	98.22 95.32 97.31	99.32 99.33 95.55
Lead V2	RE (%) PPV (%) F1 (%)	97.44 99.53 91.47	98.55 95.59 96.77	98.71 94.72 98.73	99.80 99.81 98.82	94.77 96.53 96.88	91.77 91.66 94.49
Lead V3	RE (%) PPV (%) F1 (%)	95.39 96.54 93.49	97.34 97.22 95.32	99.21 97.26 99.45	97.77 95.66 98.68	96.37 96.59 96.66	98.44 98.43 99.47
Lead V4	RE (%) PPV (%) F1 (%)	98.23 98.44 91.78	95.49 91.53 92.64	98.88 95.86 98.83	99.82 94.82 96.83	95.21 91.56 91.49	91.98 91.89 93.96
Lead V5	RE (%) PPV (%) F1 (%)	94.55 95.59 93.86	92.78 96.68 98.69	99.41 96.42 95.56	98.56 98.59 98.61	91.80 93.66 91.59	99.78 96.74 97.70
Lead V6	RE (%) PPV (%) F1 (%)	96.80 99.81 98.75	94.67 93.75 97.76	94.45 97.78 98.79	93.99 93.96 94.91	98.94 94.94 91.97	99.88 94.81 91.84

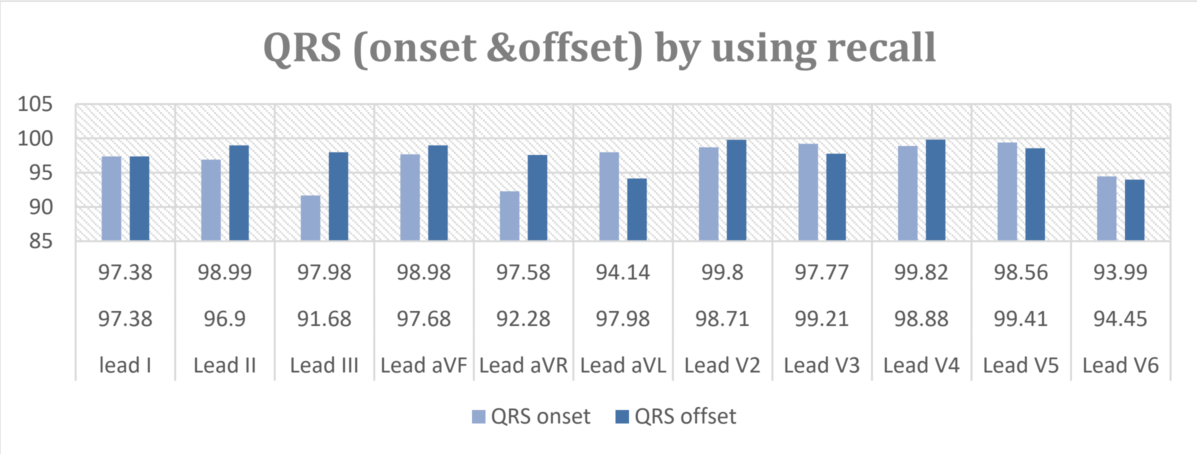

Figure 14. Summary of the result of QRST by using the recall scale

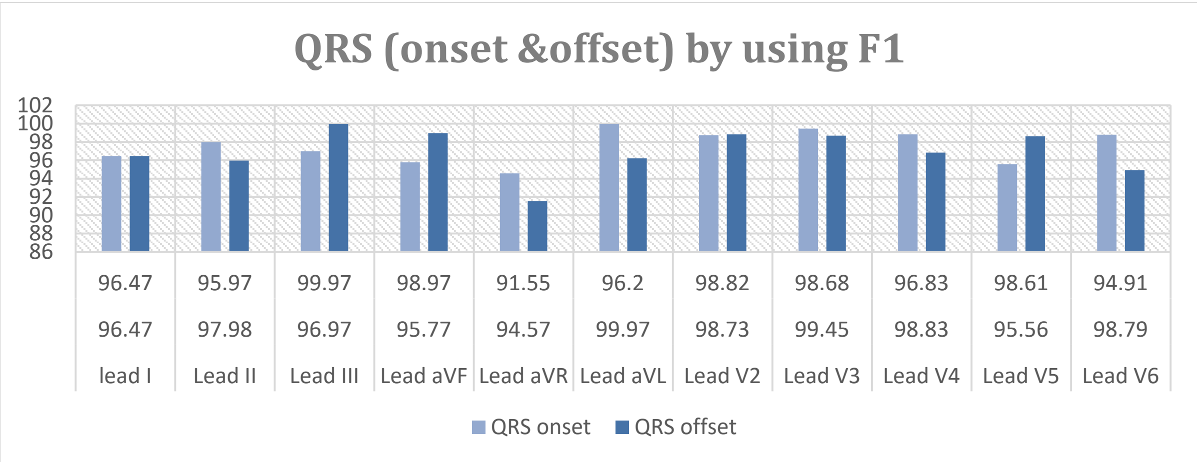

Figure 15. Summary of the result of QRST by using the F1 scale

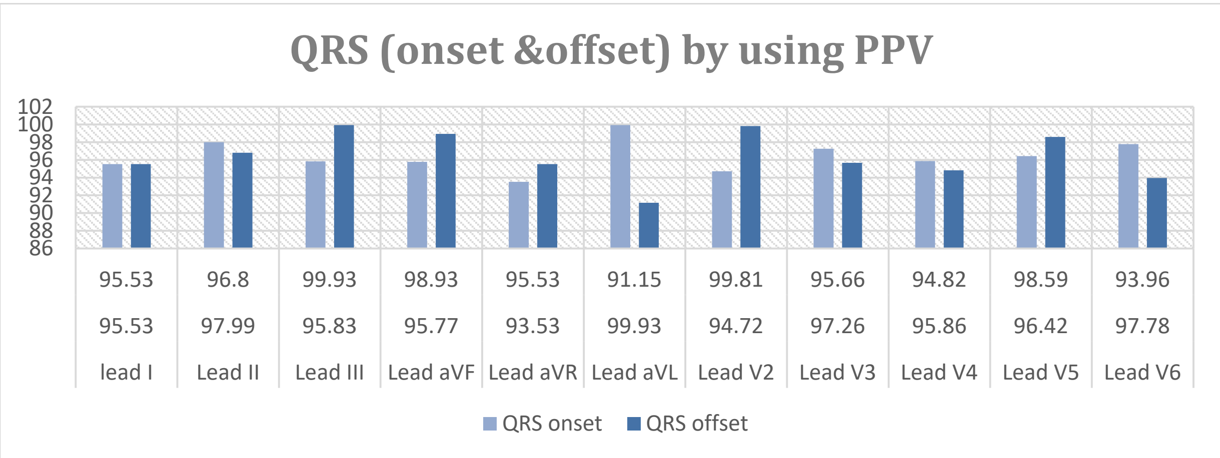

Figure 16. Summarizes the result of QRST by using the PPV scale

7. Conclusion

An electrocardiogram (ECG) is a straightforward and non-invasive diagnostic procedure that captures the heart's electrical activity, enabling the identification of disorders or the disclosure of individuals' identities. It serves several purposes in the medical domain, particularly in biometric systems.

This paper presents a method for preparing data for two purposes: segmenting the electrical signal of the electrocardiogram in a scientific manner and enabling researchers to input it into the neural network. This is necessary because this type of data is extremely large and cannot be accommodated directly as input to the neural network. The proposed approach has several stages.

The first stage is the data processing process, which takes the form of steps, including converting the data file to a CSV extension, through which one can perform (removing empty data), then resampling the signals, and as a final stage, removing the noise in these signals. These steps are considered an essential stage in the proposed approach. Through it, signals can be obtained, and the peak can be identified and extracted. The idea was to interrupt all of the p-qrs-t in the 12-lead, and as a result of this second stage, the segmentation is done through a neural network built in a way similar to U-net. The inlet and outlet sizes were equal, and the training depth with the least layers was based on experience. In future work, the approach will be developed by applying it to any data type taken from a 12-lead device and reviewing the results with the possibility of using other neural layers of the network.

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