



## A NEW METHOD FOR THE AUTOMATIC DETECTION OF VENTRICULAR AND ATRIAL PREMATURE CONTRACTIONS

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### Keywords

*Electrocardiogram,  
Atrial Premature Complex,  
Ventricular Premature  
Complex,  
Artificial Neural Networks.*

### Abstract

ECG signals used in the diagnosis of cardiovascular diseases are very important in terms of continuous recording and evaluation during the monitoring of these diseases, determination of appropriate diagnosis and treatment, and observation of possible complications. The most common disturbances among heart diseases are arising from arrhythmias. In this study, it was aimed to detect the cardiac arrhythmias APC and PVC automatically in the computer environment to provide convenience to the physician. In this context, ECG signals were first taken from the MIT-BIH Arrhythmia database and critical points P, Q, R, S, T on the signals were determined. After then, ANN was used for arrhythmia classification as APC, PVC and NSR. It was determined that the best result among the different ANN constructions was obtained with the MLPNN and the accuracy of the test was determined as 99.78% with 3-fold cross-validation and 99.89% with 10-fold cross-validation.

## KARINCİK VE KULAKÇIK ERKEN VURULARININ OTOMATİK TESPİTİNE DAYALI YENİ BİR YAKLAŞIM

### Anahtar Kelimeler

*Elektrokardiyogram,  
Erken Kulakçık Vurusu,  
Erken Karıncık Vurusu,  
Yapay Sinir Ağları.*

### Öz

Kalp-damar hastalıklarının tanısında kullanılan Elektrokardiyogram (EKG) işaretleri, bu hastalıklarının izlenmesi sürecinde sürekli olarak kaydedilip değerlendirilmeleri, uygun tanı ve tedavinin belirlenmesi ve oluşabilecek komplikasyonların gözlemlenmesi açısından oldukça önem taşımaktadır. Kalp hastalıkları arasında en sık karşılaşılan rahatsızlıklar, aritmilerden kaynaklanmaktadır. Bu çalışmada, kalp aritmilerinden olan Erken Kulakçık Vurusu (APC) ve Erken Karıncık Vurusunu (PVC) bilgisayar ortamında otomatik tespit ederek hekime kolaylık sağlamak hedeflenmiştir. Bu kapsamda, ilk olarak MIT-BIH Aritmi veri tabanından EKG sinyalleri alınmış ve sinyaller üzerinde bulunan P, Q, R, S, T kritik noktaları tespit edilmiştir. Sonrasında, Yapay Sinir Ağları (YSA) kullanılarak APC, PVC ve Normal Sinüs Ritmi (NOR) olarak aritmi sınıflandırılması yapılmıştır. Farklı YSA yapıları arasında en iyi sonucun Çok Katmanlı Algılayıcı (ÇKA) ile elde edildiği görülmüş ve sınıflandırmada test doğruluğunun 3 katlı çapraz doğrulama ile %99.78, 10 katlı çapraz doğrulama ile de %99.89 olduğu belirlenmiştir.

### Alıntı / Cite

Akın, Z. E., Bilgin, S., (2020). A New Method For The Automatic Detection Of Ventricular And Atrial Premature Contractions, Journal of Engineering Sciences and Design, 8(1), 165-174.

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### Makale Süreci / Article Process

<b>Başvuru Tarihi / Submission Date</b>	21.04.2019
<b>Revizyon Tarihi / Revision Date</b>	24.07.2019
<b>Kabul Tarihi / Accepted Date</b>	21.08.2019
<b>Yayın Tarihi / Published Date</b>	20.03.2020

### 1. Introduction

According to the report of the United Nations in 2015, the world is vis-a-vis with the aging population. According to this report, it is estimated that the number of people aged 60 and over will rise by 1.4 billion from 901 million

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in 2030 (United Nations, 2015). Depending on age progression, the cardiovascular system becomes weaker and more susceptible to diseases.

Electrocardiogram (ECG) is one of the most important methods used in the diagnosis of cardiovascular disease. ECG is a type of bioelectric signal obtained by recording the electrical activity of the heart with time. Heart arrhythmias, one of the most common disorders on the heart, also cause many diseases at the same time. Therefore, early diagnosis and treatment of arrhythmias are very important. Arrhythmias are detected by the interpretation of ECG signals taken from the heart by physicians. It, in particular, is frequently used to monitor the amplitude and duration of waves on the ECG, to identify the conduction in the heart, and to identify patients who are the arrhythmia. The types of heartbeat classified in the study are Normal Sinus Rhythm (NSR), Atrial Premature Complex (APC) and Ventricular Premature Complex (PVC). NSR is the reference physiological rhythm of the heart and it is defined as the delivery of the stimulus initiated by the Sinoatrial (SA) node to the myocardium with a correct timing through the cardiac conduction system. The PR interval is between 120 and 200 ms, while the heart rate is between 60 and 100 beats per minute (Goldberger, 2006). APC occurs as a result of premature contraction of the atria with rising stimulation from an ectopic focal in the left or right atrium. P wave in APC arrhythmias is seen earlier than expected. PR interval can from normally short or long depending on the location of the stimulus and of the atrioventricular (AV) node response, while heart rate may vary depending on APC frequency (Goldberger, 2006). PVC occurs as a result of premature contraction of ventricles with rising stimulation from an ectopic focal under the AV junction. PVCs are beats that precede the expected sinus rhythm, have wide QRS complexes and frequently are observed in the QRS complex of P waves. Generally, APCs have similar morphological characteristics such as normal sinus beat, while PVCs have a large degree of change in the QRS complex (Goldberger, 2006). Since the interpretation of ECG signals is a time consuming and demanding process for physicians, detailed analysis and interpretation software that gives the same result as the diagnosis of the physician at high rates by interpreting these signals in the computer environment is being developed and its usage is increasing (Elhaj et al., 2016).

## 2. Literature Survey

Some studies about this classification are available in the literature. The automatic detection of the five basic waves (P, Q, R, S and T), which are produced in the ECG as a response to each heart rate and together with the ECG signal, are very important for cardiovascular evaluation. For example, it allows the diagnosis of cardiac arrhythmias (Tsipouras, et al., 2002; Tran, et al., 2004; De Chazal, et al., 2004; Krasteva, et al., 2006), monitoring of autonomic cardiovascular system changes during sleep and hypertension (Scholz, et al., 1997; Trinder, et al., 2001), shortness of breath such as obstructive sleep apnea syndrome (Zapanta, et al., 2004; Shouldice, et al., 2004) and monitoring of other structural or functional cardiac disorders. The detection of QRS complexes and R hills has been extensively studied over the last two decades (Elgendi, et al., 2014). However, T wave detection was not investigated as comprehensively as the perception of QRS complexes and it was observed that there were still problems with its perception (Goutas, et al., 2005; Wan, et al., 2010; Vazquez-Seisdedos, et al., 2011; Nair and Marziliano, 2014). Whereas accurate detection of T waves is necessary to establish various diagnoses such as acute coronary syndrome (Hayden et al., 2002), acute myocardial infarction (Michael et al., 2002) or potentially fatal arrhythmias (Smith et al., 2010). There are many studies in the literature on the automatic diagnosis of arrhythmias in ECG beats (Luz et al., 2015). In these studies, it was observed that classification processes were mostly made by pattern recognition approaches based on Artificial Neural Networks (ANN) (Yang et al., 2017; Rahhal et al., 2018). At this point, the structure differentiating similar studies from each other is feature extraction methods and different classification algorithms. Polat and Gunes used Principal Component Analysis for the arrangements related to the size of the data set and determined whether there was an arrhythmia in the ECG data using the Smallest Square Support Vector Machine for the diagnosis of arrhythmia. The obtained classification accuracy was calculated as 96.86%, 100% and 100% (Polat and Gunes, 2006). In the ECG signals obtained from the Massachusetts Institute of Technology – Beth Israel Hospital (MIT-BIH) arrhythmia database, among studies based on the automatic detection of APC were generally classified by examining the morphology of the signal (Luz et al., 2005; García et al., 2011; Martis et al., 2012; Ravindra and Dhuli, 2017). Chiu and his team demonstrated a study based on the morphological features of arrhythmias. In their study, they used an experimental group with a healthy group existent NSR and a group of patients existent APC and PVC arrhythmias. Firstly, the QRS complexes on the ECG signals of the subjects were determined by the QRS capture algorithm and then they calculated the similarity of the arrhythmias by using the correlation coefficient and RR intervals. Finally, the algorithm was tested using the MIT-BIH arrhythmia database and the sensitivity was calculated 99,81% for NSR, 81,82% for APC and 95,83% for PVC (Chiu et al. 2005). In the studies, it was seen that Support Vector Machine is generally used in the stage of classification of arrhythmias (Alajlan et al., 2014; Kaya and Pehlivan 2015; Chen et al., 2017; Kumar et al., 2017; Li et al., 2017; Chetan et al., 2018; Hajeb-Mohammadalipour et al., 2018; Raj and Ray 2018). A&F Jovic applied Alphabet entropy, a recently developed symbolic dynamic method into heart rate variability analysis to improve automatic classification (Jovic A&F, 2017). In our previous study on the subject, the accuracy value of

APC, PVC and NSR classification using Discrete Wavelet Transform (DWT) energy levels and Linear Discrimination Analysis (LDA) was obtained as 96.7% (Akin and Bilgin, 2017).

As seen in the literature, there are studies on the classification of different arrhythmias by different methods. However, these studies have different purposes. Some studies classify arrhythmias as normal beat or arrhythmic beat, and some studies classify different arrhythmias, separately. However, when the accuracy rates are examined, according to the purposes of the studies, only 99% accuracy is obtained in the classification of arrhythmia and 98% accuracy in the classification between each other. The aim of this study is the determination of the critical points of P, Q, R, S, T in ECG signals and APC, PVC, NSR arrhythmia classification. Also, the novelty of the study is the use of WQRS, TQ, pb1 and pb2 parameters playing an important role in APC, PVC, NSR classification. These parameters are explained in the feature extraction section of the study. In addition, they are part of the study can be considered as innovative.

### 3. Material and Method

In the study, firstly ECG records were taken from the MIT-BIH arrhythmia database. These signals passed through the pre-processed to remove the noises present on the received records. Subsequently, the feature extraction was performed on the ECG signal for both the detection of critical points and the classification of arrhythmias. P, Q, R, S and T points on the signals were determined with the extracted attributes. At the last stage, arrhythmia classification has been done using different ANN structures according to the beat types APC, PVC and NSR.

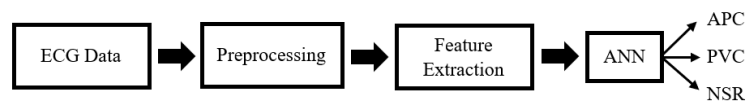


Figure 1. Block diagram of the study

#### 3.1. Database

When the ECG records used in the study were taken from the MIT-BIH Arrhythmia database on Physionet website (Moody and Mark 1990; Goldberger et al., 2000; Anonymous, 2018). The MIT-BIH Arrhythmia database contains half-hour citations of 24-hour ECG recordings, recorded as 48 two-channel recordings, between 1975 and 1992. The records are digitized with 360 Hz sampling frequency at 10 mV intervals and 11-bit resolution per channel after being passed through a filter that has a band of 0.1-100 Hz (Moody and Mark, 2001). For the reliability of ANN, it is so important that the number of datasets in classes is homogeneous. Therefore, data numbers were determined according to arrhythmias beats having the lowest number in the database.

#### 3.2. Pre-processing

Noises analysis on the ECG signal makes difficult and reduces the success of the algorithm. For this reason, the signals are passed the pre-processing in the first stage. In the study, firstly, Savitzky-Golay Filter (SGF) with 2nd order and window size 25 was used to suppress high-frequency components on the signals from the database (Fig.2.). Following Band Pass Filter (BPF) with 7 and 28 Hz cut-off frequencies were then applied to filter the low-frequency noises. Finally, a High Pass Filter (HPF) with a cut-off frequency of 40 degrees and 4.9 Hz was used to remove the baseline slip found in the ECG signal, so that the base level on the signal was equalized. These steps are described in detail in our study about a new QRS detection algorithm (Bilgin and Akin, 2018).

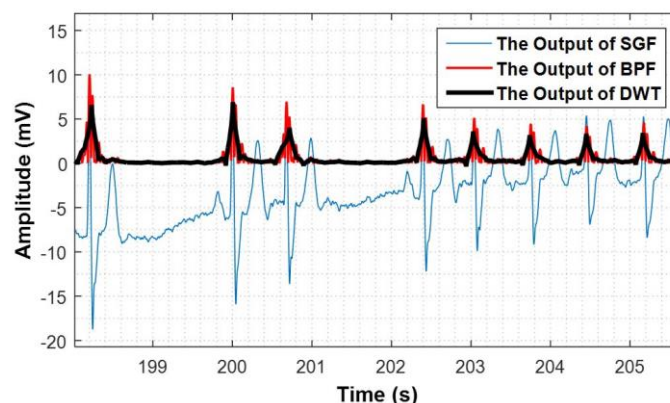


Figure 2. The SGF and DWT output on the ECG

### 3.3. Feature Extraction from ECG Signal

The QRS detection algorithm (Bilgin and Akin, 2018) is used to capture these points in the QRS region. On the captured QRS regions, the peak search algorithm was used and the parts below the specified threshold were subtracted from the signal and the components with the highest amplitude in the remaining parts were searched with specific window intervals and the peak points was determined. So, the R peak values of the signal have been reached (Fig. 3.). In the study, it was tried to catch points Q, R and S first for the automatic detection of critical points.

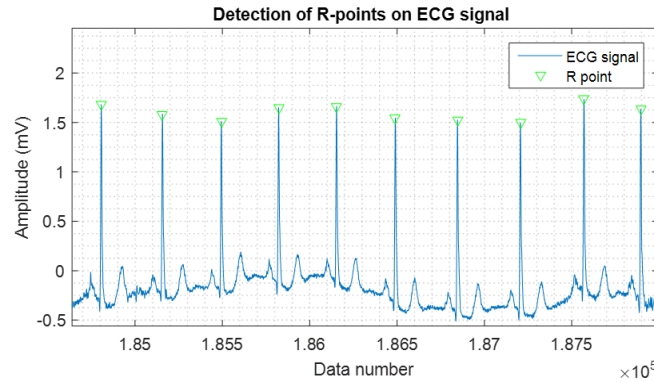


Figure 3. Detection of R points on ECG signal

The QRS height and RR intervals were determined as the feature for the detection of other critical points relative to the obtained R peaks as seen in Fig. 4.

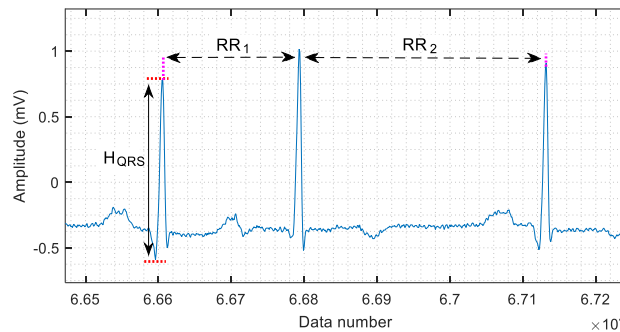


Figure 4. Features extracted for the detection of critical points

After the detection of the R peaks on the ECG signal, the signal RR intervals for the detection of Q and S points were analyzed after being cut off. As shown in Fig. 5., in order to detect S and Q points on the cut parts, the RR intervals were separated into regions and the extremum points were looked at with zero crossings on these regions. The zero crossing is used to detect if a signal in each channel cross zero. For this firstly the function  $P_k(T)$  is calculated. This function is an expression of the discrete distribution of zero-crossing interval durations for the signal  $u(t)$ , in some observation window  $r_k$  as a function of zero-crossing interval duration  $T$ . The function  $P_k(T)$  may be mathematical as;

$$P_k(T) = \sum_{i=1}^{M_k} \delta(T - T_{ki}) \quad (1)$$

where  $\delta(x)$  is the known Dirac delta function.  $M_k$  is defined as the number of zero-crossings which have occurred in a time interval of length  $r_k$ . A count of the total number of zero-crossings in a time window is exactly equivalent to a count of the total number of zero-crossing intervals in the time window. Such a count can be obtained by integrating  $P_k(T)$  over its entire range. Then, normalizing by the duration of the observation window will provide  $Z_k$ . In this way, zero crossing function is expressed by,

$$Z_k = \frac{1}{r_k} \int_{T_0}^{T_L} P_k(T) dT \quad (2)$$

where,  $[T_0 T_L]$  is defined as the range of zero crossing interval durations possible (Niederjohn, 1975). The first derivative of the dt1 signal in Fig. 5., is the calculated second derivative after zero-crossing the dt1 signal at dt2.

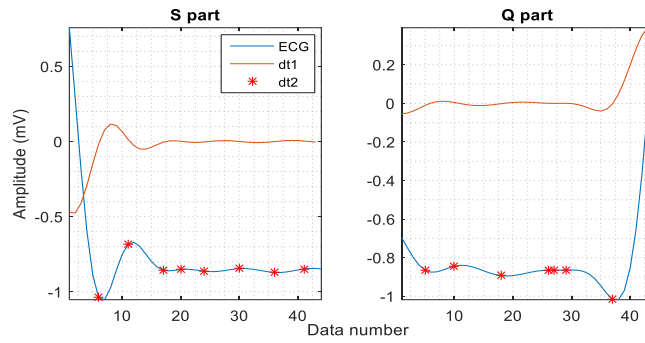


Figure 5. S and Q parts obtained from RR intervals

In the signals, the R-peak in each cycle was referenced, and the extremum point that precedes this peak was the Q-point while the extremum point that follows this peak was determined as the S-point. In this way, Q and S points were determined on the signals. (Fig. 6).

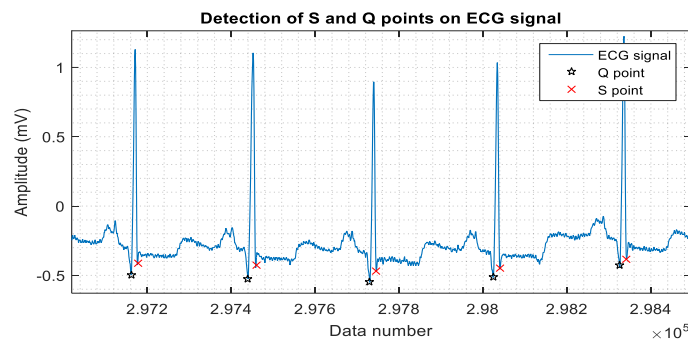


Figure 6. Detection of S and Q points on ECG signal

For the determination of the P and T points between the critical points, the signal was analyzed by cutting from the point S belonging to the previous beat to the point Q of the next beat. On the cut parts, as in the detection of Q-S points, the P region has seen in Fig. 7. was determined and the extremity points were evaluated by taking the derivative from the 2<sup>nd</sup> order. The starting point of both the P point and the P wave was detected via the extremity points. Where dt is the extremity points in the P region, P1 is the point P, and P2 is the starting point of the P wave.

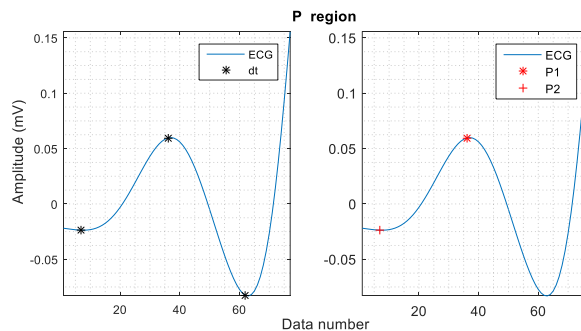


Figure 7. The P region obtained from the SQ part

The same procedure was applied for point T. So, the start/end points of P and T are seen in Fig. 8.

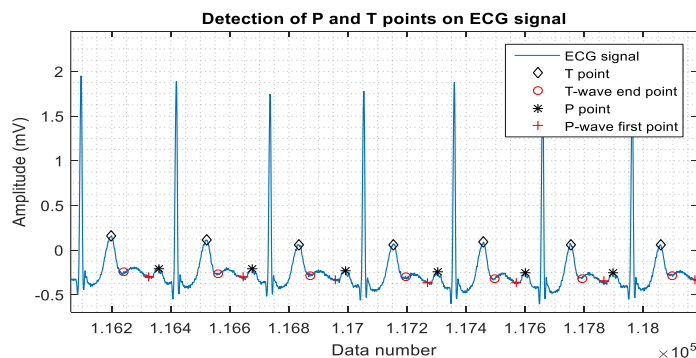


Figure 8. Detection of P and T on ECG signal

Finally, extracted features are shown in Fig. 9.

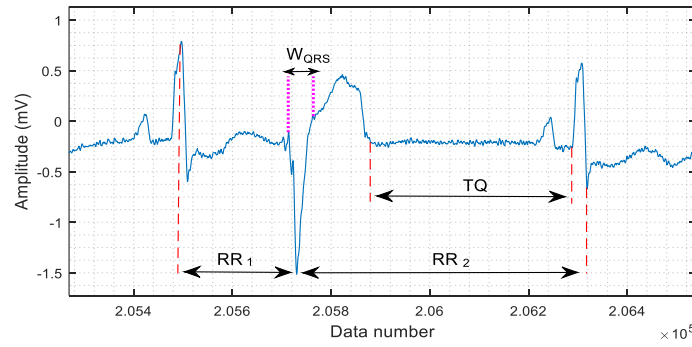


Figure 9. Extracted features for classifying arrhythmias

### 3.4. Artificial Neural Networks (ANN)

ANN are computer systems that are made up of interconnected artificial neural cells, which determine the relationships between events from the samples and then use the information they learn about the samples that they have never seen before. ANN structures are generally used in arrhythmia classification. Therefore, considering the literature, the most prominent choice is the use of ANN (Luz et al., 2015). The information that ANN possesses is stored in the network with the weight values in the connections with each processing element and spread over the network (Hu and Hwang, 2002). Three different ANN structures consisting of MLPNN, Radial basis function neural network (RBFNN) and General regression neural network (GRNN) are applied during the study. Multilayer perceptron neural network (MLPNN) consists of an input layer where information input is made, one or more hidden layers and an output layer (Hu and Hwang, 2002). The output of the MLPNN network structure is as follows,

$$y = f\left(\sum_{i=1}^N X_i W_{ij} + b_j\right), \quad (j = 1, 2, \dots, M) \quad (3)$$

In this equation,  $M$  is the number of layers, the number of neurons in the input layer has been denoted by  $N$ ,  $X_i$  refers to the  $i^{\text{th}}$  neuron in a hidden layer,  $W_i$  is explained as weights for each input,  $b_j$  is the bias of the perceptron,  $f$  is the activation function, and  $y$  is the output of the perceptron in the  $j^{\text{th}}$  layer. RBFNN is a model of ANN consisting of an input layer, a core layer and an output layer. Input variables are passed directly through the nodes in the input layer and are connected to the core layer without weight (Hu and Hwang, 2002). GRNN is an ANN structure consisting of an input layer, a pattern layer, an additional layer, and an output layer. It has a dynamic network structure that uses regression analysis (Specht, 1991). Besides, Decision Tree (DT) method was applied alternatively. DT, which uses a multistage or sequential approach to the realization of the classification process, divides the data into subcategories in order to determine the relationship in the data. The basic structure of DT consists of three basic parts called nodes, branches and leaves (Goetz, 2010). In the study, four features were determined for the inputs of the ANN model used in APC, PVC and NSR classification (Fig. 10.). These features are WQRS, TQ, pb1 and pb2. WQRS is defined as QRS width (time difference between point S and point Q). TQ is the time difference between the end point of T and the next point Q (Fossa, 2006). pb1 and pb2 features are explained as RR2/RR1 and RR2-RR1 respectively. The most important novelty of this study is explained in this part. WQRS, TQ, pb1 and pb2 parameters being a distinguishing feature were not used for this type of classification in the previous studies (Akin, 2018).

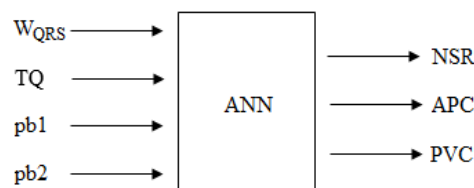


Figure 10. ANN structure used in the study

The determined features were analyzed with different ANN structures and the results were observed. In MLPNN, the Levenberg-Marquardt algorithm was used as the backpropagation training error method to select the weight matrix. Other parameters of the applied ANN constructions are as in Table 1.

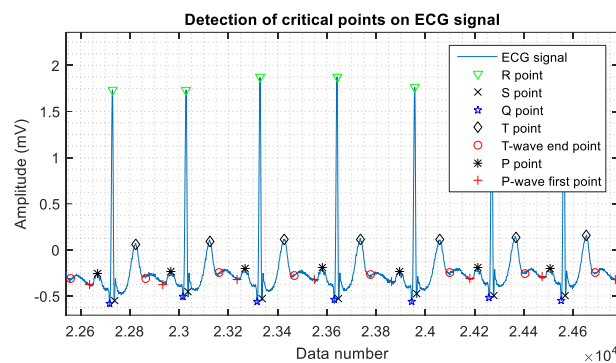
**Table 1.** The Characteristics of the implemented ANN structures.

<b>MLPNN</b>	Number of hidden layers	2
	Number of neurons	[10 10]
	Transfer function	tansig
	Learning function	trainlm
	Learning rate	0.1
	Momentum constant	0.3
	Goal	0.001
<b>RBFNN</b>	Spread parameter	0.9
	Goal	0.001
<b>GRNN</b>	Spread parameter	0.1
	Goal	0.001

The homogeneous distribution of the data used in the ANN procedure is so important for the reliability of the study. Therefore, data numbers were selected based on the lowest number of arrhythmias beats in the database. 300 beats from each arrhythmia type were included in the study so that the numbers of groups are equal to each other. Four features of each beat were applied to ANN entries.

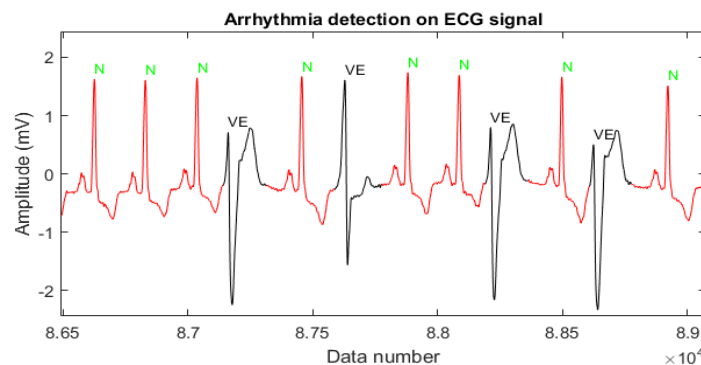
#### 4. Experimental Results

The critical points on the ECG signals received from the MIT-BIH arrhythmia database have been detected as shown in Fig. 11.



**Figure 11.** Detection of critical points on ECG signals

In the study, for the performance evaluation of the detection of critical points, the results of the QRS detect algorithm are referenced. In the performance evaluation of QRS detect algorithm, sensitivity, positive predictive rate, the detection error rate and accuracy values were used and when the results were observed, the overall accuracy value of the algorithm was determined as 99.74% (Bilgin and Akin, 2018). In this study, Q, R and S points were detected by 100% accuracy in each QRS window which is detected correctly. Similarly, since P and T points are cut into pieces and analyzed, they were determined that these points were detected with 100% accuracy upon the correct capture of R point. For the classification of APC and PVC arrhythmias, primarily normal beat and early beat were detected using pb1 (RR2 / RR1) value as shown in Fig. 12. Where, N represents normal beats, while VE represents early beats. As seen in the figure, both APC and PVC arrhythmias were captured with VE. While, the second VE is an APC arrhythmia, the first, third and fourth VEs are PVC arrhythmias.



**Figure 12.** Arrhythmia detection on ECG signal

For discriminating APC and PVC arrhythmias via the VEs, ANN was used. NSR, APC and PVC classification were accomplished with ANN and results obtained in different parameters were observed with K-Fold-Cross-Validation (K-FCV) (Table 2). Training and Testing percentages in the database are chosen as 65% and 35% respectively in ANN applications in the literature (Looney, 1996). Therefore, the selection of the most suitable Cross validation method is 3-FCV (Three Fold Cross Validation) method in order to provide this ratio. As a result, TFCV method is preferred for validation of the methods in this study. On the other hand, in the 10-FCV, Training and Testing percentages are selected as 90% and 10% respectively in ANN applications in the literature.

**Table 2.** 3-FCV and 10-FCV results for NSR, APC and PVC.

Validation	Methods	Results		
		Sens. (%)	Spec. (%)	Acc. (%)
3-FCV	MLPNN	99.67	99.67	99.78
	RBFNN	96.45	98.33	98.22
	GRNN	97.02	97.32	98.11
	DT	99.35	99.67	99.67
10-FCV	MLPNN	100.00	99.68	99.89
	RBFNN	96.55	98.68	98.33
	GRNN	97.35	97.38	98.22
	DT	99.68	99.68	99.78

## 5. Result and Discussion

In this study, the detection of the critical points in ECG recordings obtained from the MIT-BIH arrhythmia database and was made by arrhythmia classification according to NSR, APC and PVC beats. In the pre-processing part of the study, SGF, BPF and HPF were applied to the ECG signal and the signals were prepared for feature extraction. Then, for the determination of both critical points and for the classification of arrhythmias, feature extraction was made via ECG signal. In the classification of NSR, APC and PVC beat, ANN was chosen as the most widely used technique in the literature as a classifier model. The WQRS, TQ, pb1 and pb2 features extracted from the ECG signal are defined as ANN inputs. These features were analyzed with different ANN structures and the results obtained with different parameters were observed with K-FCV. When the results obtained from the study were evaluated, for the success of the critical points was referenced the success of the QRS detect algorithm. According to this, an accuracy of 99.74% was obtained over the 109468 QRS in the database. Within each determined QRS window, the signals were scanned with eye and the Q, R and S points were observed to detect with 100% accuracy. In the same way, P and T points were analyzed by cutting into pieces, and it was determined that these points were determined with 100% accuracy upon correct detected of point R. When the success of arrhythmia classification was observed, it was seen that the best results were obtained with MLPNN in the NSR, APC and PVC classification between the different ANN structures and it was determined that the test accuracy was 99.78% with 3-FCV and 99.89% with 10-FCV. In the study, an original QRS detection algorithm was used to find critical points and the captured points were developed via this algorithm. Analysis based on the determination of critical points and the features used in arrhythmia classification is again based on this algorithm and combined with other methods. This case reveals the originality of the study. According to the results, this study is thought to be an important alternative to facilitate the diagnosis process by acting as a second clinician as a computer-aided analysis and interpretation software in cardiology. Considering this case, If the algorithm in this study is integrated with a computer interface, the interface will be at a level that will automatically detect APC, PVC and NSR on long-term recorded ECG data.

When the results were evaluated, it was observed that the best NSR, APC and PVC classification was 99.89% test accuracy in MLPNN with 10-FCV. Previously, the accuracy of the NSR, APC and PVC classification study, which is based on DWT energy levels was obtained as 96.7% (Akın and Bilgin, 2017). In this study, 4 important features were extracted and the classification is realized according to these characteristics.

As seen in the literature, there are some studies being interested in the classification of different arrhythmias using different methods. However, these studies have different purposes. Alajlan et al. have classified PVC and non-PVC and have achieved a total accuracy of 94.15% (Alajlan et al., 2014). Al Rahhal and his team made only PVC classification in their study. They achieved 98.6% accuracy in the classification using multichannel ECG (Rahhal et al., 2018). Kaya and Pehlivan made PVC classification and achieved 99.63% accuracy (Kaya and Pehlivan 2015). Yang and his team tried to determine the localization of PVC using CNN (Yang et al., 2017). These types of studies classify arrhythmias as binary classification (normal or abnormal beats), and other similar studies classify different arrhythmias separately. However, while the studies focusing on the binary classification obtain approximately 99% accuracy, the others including multiple classifications have about 98% accuracy. The aim of this study is the determination of the critical points of P, Q, R, S, T in ECG signals and APC, PVC, NSR arrhythmia classification. Therefore, the novelty of the study is to determine WQRS, TQ, pb1 and pb2 parameters being so important for APC, PVC, NSR discrimination. In addition, the feature extraction part of the study can be considered as a novel.



## Acknowledgement

This study was supported by Medises Medical and Electronics Co. in Antalya, Turkey (grant number TEYDEB-7151338).

## Conflict of Interest

No conflict of interest was declared by the authors.

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