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AN EFFICIENT ARRHYTHMIC HEARTBEAT CLASSIFICATION METHOD USING ECG MORPHOLOGY BASED FEATURES

EKG MORFOLOJİSİNE DAYALI ÖZELLİKLERİ KULLANAN ETKİLİ BİR ARİTMİK KALP ATIŞI SINIFLANDIRMA YÖNTEMİ

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ABSTRACT

Clinically, analyzing the ECG records is often quite time-consuming. Therefore, it is important to perform rapid analysis and detect abnormalities in ECG signals such as arrhythmias. For this reason, computer-aided diagnostic systems are being developed. With the developed systems, abnormalities in the ECG record can be easily detected. Thus, the developed systems are useful for clinicians in determining the diagnosis and treatment methods of heart diseases. In this study, an IIR based elliptic digital filter was used for removing the baseline wander in the ECG signal. Morphologically based features of the ECG signal are extracted. Then, the most meaningful of these features were selected by using the SelectKBest method and the f_ classif score function. Five basic arrhythmias labelled according to the AAMI standard have been classified using machine learning methods utilizing these feature data sets. Logistic Regression (LR), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) and Multi Layer Perceptron (MLP) machine learning methods were used as classifiers for arrhythmia diagnosis. The performance results obtained with these classifiers were examined and the LR method, which predicts the five basic arrhythmias as satisfactorily high was proposed as a classifier. The performance results of the LR method were obtained as Accuracy 99.766%, Sensitivity 99.416%, Specificity 99.854% and F1-Score 99.416%. In this study, the arrhythmia diagnosis method has been proposed which predicts five basic arrhythmias satisfactorily high. The proposed method can be used beneficially in computer-aided diagnostic systems. In this study, Google Colaboratory was used for the software and hardware needs of machine learning methods.

Keywords: Cloud Computing, Feature Extraction, Google Colaboratory, Machine Learning Methods, Signal Processing

ÖZET

Klinik açıdan ECG kayıtlarının analiz edilmesi çoğu zaman oldukça zaman alıcı olmaktadır. Bu nedenle, hızlı analiz yapmak ve ECG sinyallerindeki aritmi gibi anormallikleri tespit etmek önem arz etmektedir. Bu nedenle bilgisayar destekli teşhis sistemleri geliştirilmektedir. Geliştirilen sistemler vasıtasıyla ECG kaydında bulunan anormallikler kolaylıkla tespit edilebilmektedir. Böylece, geliştirilen sistemler kalp hastalıklarının teşhis ve tedavi yöntemlerinin belirlenmesinde klinisyenlere karar verme aşamasında faydalı olmaktadır. Bu çalışmada, ECG sinyalindeki baseline wander'ı kaldıran bir IIR tabanlı elliptic digital filtre kullanılmıştır. ECG sinyalinin morfolojik tabanlı öznitelikleri çıkartılmıştır. Daha sonra, SelectKBest yöntemi ve f_ classif skor fonksiyonu kullanılarak bu özniteliklerden en belirleyici olanları seçilmiştir. AAMI standardına göre etiketlenmiş beş temel aritmi, bu öznitelik veri setleri kullanılarak makine öğrenimi yöntemleriyle sınıflandırılmıştır. Aritmi teşhisi için Logistic Regression (LR), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) ve Multi Layer Perceptron (MLP) makine öğrenmesi yöntemleri sınıflandırıcı olarak kullanılmıştır. Bu sınıflayıcılarla elde edilen başarım sonuçları incelenmiş ve beş temel aritmiyi tatmin edici derecede yüksek olarak tahmin eden LR yöntemi sınıflayıcı olarak önerilmiştir. LR yöntemine ait başarım sonuçları Accuracy 99.766%, Sensitivity 99.416%, Specificity 99.854% and F1-Score 99.416% olarak elde edilmiştir. Bu çalışmada, beş temel aritmiyi tatmin edici derecede yüksek olarak tahmin eden bilgisayar destekli teşhis sistemlerinde faydalı bir şekilde kullanılabilecek bir aritmi teşhis yöntemi önerilmiştir. Bu çalışmada, makine öğrenmesi yöntemlerinin ve özellik seçimi yönteminin gereksinim duyduğu yazılım ve donanım ihtiyacı için Google Cloud Computing alt yapısını kullanan Google Colaboratory'den faydalanılmıştır.

Anahtar Kelimeler: Bulut Bilişim, Öznitellik Çıkartma, Google Colaboratory, Makine Öğrenimi Yöntemleri, Sinyal İşleme

1. INTRODUCTION

Analyzing the ECG signal is very important in diagnosing cardiac diseases and determining treatment methods. The ECG signal provides information to clinicians and healthcare professionals about the electrical activity of the heart. In any undesirable situation that occurs in the electrical signal transmission of the heart or in the vessels feeding the heart muscles the ECG signal takes a different form other than its normal form. By examining these changes in the ECG signal, doctors can diagnose abnormalities in the heart. Extensive ECG recordings take a long time to review and require a lot of attention. For this reason, decision support systems are developed for doctors and healthcare professionals to detect changes in the ECG signal. Computer-aided diagnostic methods analyzing ECG records and contributing to the diagnosis and treatment process are recommended. Machine learning methods detecting arrhythmias in the ECG signal have been developed. Studies in the literature are given below.

Chazal and Reilly proposed a method enabling the local classifier to learn as fast as possible to minimize the specialist cardiologist intervention (Chazal and Reilly, 2006). Jiang and Seong proposed an evolutionary optimization of block-based neural networks feed-forward application and its application in personalized ECG heartbeat classification (Jiang and Seong, 2007). Matis et al. obtained features from the ECG signal using the principal component analysis technique. They made the arrhythmia classification with the Least Square-Support Vector Machine (LS-SVM) method using these features (Martis et al., 2013). Raj extracted the features from the ECG signal using the Double Density Complex Wavelet Transform (DDCWT) method. The Artificial Bee Colony (ABC) and Twin Support Vector Machine methods have classified the ECG signal into five categories using these features (Raj, 2020).

In this study, MIT-BIH AD ECG recordings were used for the diagnosis of arrhythmia. An elliptic digital filter has been developed to remove baseline wander noise from the ECG signal. Morphology-based features were extracted from the ECG signal. Then, the most meaningful of these features were selected by the SelectKBest method. Logistic Regression (LR), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) and Multi Layer Perceptron (MLP) machine learning methods were fed by obtained features and arrhythmia diagnosis was made. The performance results of machine learning methods were evaluated. A highly performing arrhythmia diagnosis method useful for a computer-aided diagnosis system has been proposed.

2. MATERIAL AND METHODS

2.1. Data Set

The MIT-BIH Arrhythmia Database (MIT-BIH AD) (Moody and Mark, 2001; Yakut, 2018; Yakut and Bolat, 2018; Yakut et al., 2018; Yakut et al., 2016), accepted as a standard tool to test the developed algorithms or proposed methods for classifying arrhythmia types, was used. The MIT-

BIH AD consists of 48 ECG records of 30 minutes collected from 47 patients. These records are taken from over 4000 long-term holter records from inpatients (about 60%) or outpatients (about 40%). Twenty-three records include a representative set of normal sinus rhythms and routine arrhythmias. The other twenty-five records have less common but clinically significant cardiac abnormalities. Each ECG record has an annotation file that specifies the location of the R-peaks and the class label as a reference for each heartbeat. These files were annotated independently by two or more cardiologists.

ECG records were digitized with 360 samples at amplitude of 10 mV with an 11-bit resolution (Mark and Moody, 2020; Yakut, 2018). In this study, data sets for training and testing were prepared with obtained ECG records using MIT-BIH AD. Figure 1 summarizes the way in which data sets were prepared.

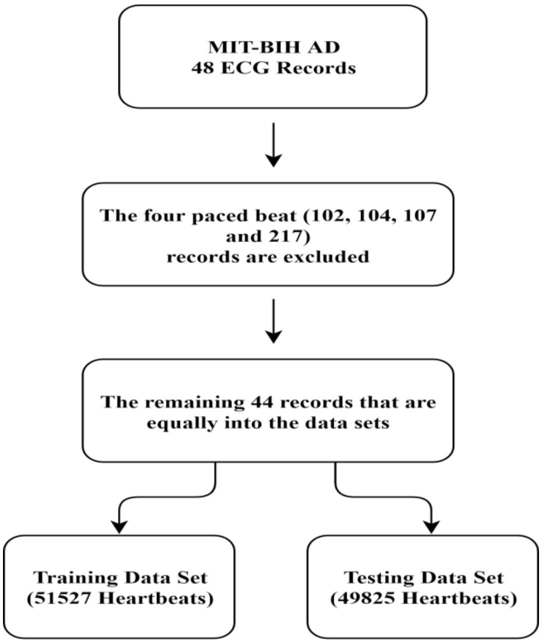

Figure 1. MIT-BIH AD was divided into training and testing sets (Yakut, 2018)

Table 1. Distribution of heartbeats for training and testing data sets

The label of AAMI standard	The label of MIT-BIH class	Total	Training	Testing
N	N, L, R, e, j	90083	45845	44238
S	A, a, J, x	2972	1000	1972
V	V, !, E	7480	4260	3220
F	F	802	414	388
Q	Q	15	8	7

The five heartbeat classes recommended by AAMI standard is presented in Table 1.

Heartbeats of MIT-BIH AD are labelled in five basic classes according to AAMI (EC57, 1998) standard (Yakut, 2018).

1. Class N (normal and bundle branch block beat types) corresponding to beats originating from the sinus node,

2. Class S, corresponding to supraventricular ectopic beats (SVEB),

3. Class V corresponding to ventricular ectopic beats (VEB),

4. Class F corresponds to pulses caused by the fusion of normal and VEBs,

5. Class Q corresponding to unknown beats, including non-contact beats.

2.2. ECG Signal Preprocessing

In this study, a lowpass elliptic digital filter was used to remove the baseline wander noise from ECG recordings in MIT-BIH AD. Elliptic Infinite Impulse Response (IIR) filter is a type of digital filter which contains identical wavelets and the number of which can be changed independently in the passband and stopband. The transition zone is shorter compared to another filter of the same degree.

Figure 2 shows the steps of applying the filter that removes the baseline wander noise from the ECG signal. In this study, a low pass elliptic digital filter that does not pass noise below 1 Hz (Yakut et al., 2018) was implemented. ECG record number 101 taken from MIT-BIH AD in Figure 2 (A) is used as an example. The ECG signal number 101 in Figure 2 (A) is filtered through a lowpass elliptic digital filter. The noisy signal obtained as a result of this process is shown in Figure 2 (B). The ECG signal which is cleaned from baseline wander noise is shown in Figure 2 (C). When Figure 2 (C) is examined, it is observed that the filtered ECG signal fits the baseline.

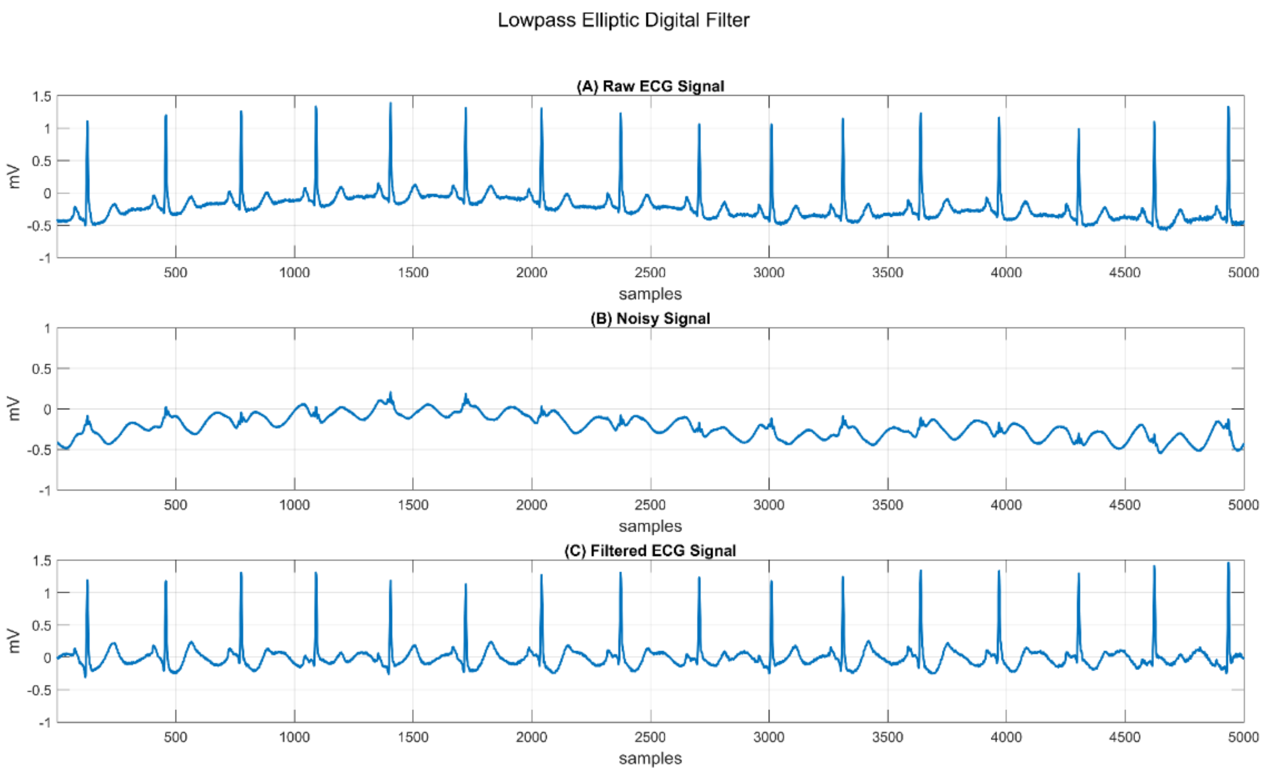

Figure 2. Removing of ECG signal noise with lowpass elliptic digital filter (101th ECG signal)

2.3. Morphology-Based ECG Features

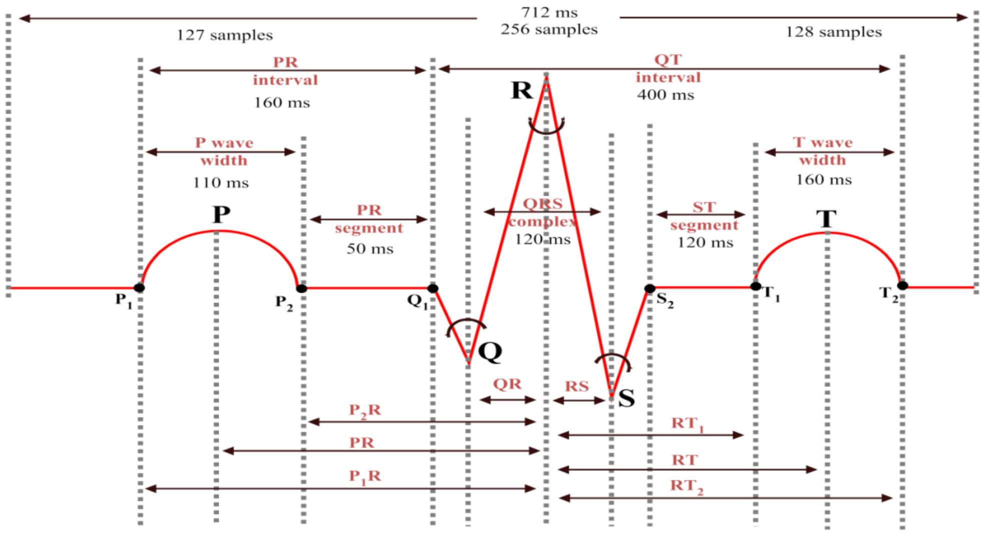

Figure 3. Extracting the morphological features of a heartbeat components of the ECG signal using the time window (Yakut, 2018)

Features obtained using the morphological structure of the ECG signal, detailed in Figure 3 are (Yakut, 2018);

(i) Temporal features, which are the temporal differences between the significant/fiducial points of the ECG signal,

(ii) Amplitude features between the significant/fiducial points of the ECG signal, and

(iii) Angular features between the significant/fiducial points of the ECG signal.

The obtained list of features is given in Table 2.

Table 2. Morphological features extracted from the ECG signal

Number of features	Description of features	Number of features	Description of features
1	P width	20	PR amplitude
2	PR	21	QR amplitude
3	P_1R	22	R amplitude
4	P_2R	23	RS amplitude
5	PR interval	24	T amplitude
6	PQ	25	RT amplitude
7	PS interval	26	QR area
8	PT	27	RS area
9	QR	28	$\angle$ Q_1QR angle
10	QS	29	$\angle$QRS angle
11	QT interval	30	$\angle RSS_2$ angle
12	QRS interval	31	Pre RR
13	RS	32	Post RR
14	RT_1	33	RR average
15	RT	34	RR local average
16	RT_2	35	IR time information
17	ST interval	36-47	Amplitude of the ECG fiducial points
18	T width	48-57	Interval of fiducial ECG points
19	P amplitude		

The Heart Rate is the ratio at which shows the number of heartbeat per minute. Heart Rate Variability (HRV) is defined as the time interval between successive heartbeats. HRV, known as the RR interval, is the period between the two R peaks (Yakut et al. 2014; Yakut, 2018), and shown in Figure 4. It is calculated as given in Eq. (1) (Yakut et al. 2014; Yakut, 2018).

$$RR(i) = R(i+1) - R(i) \tag{1}$$

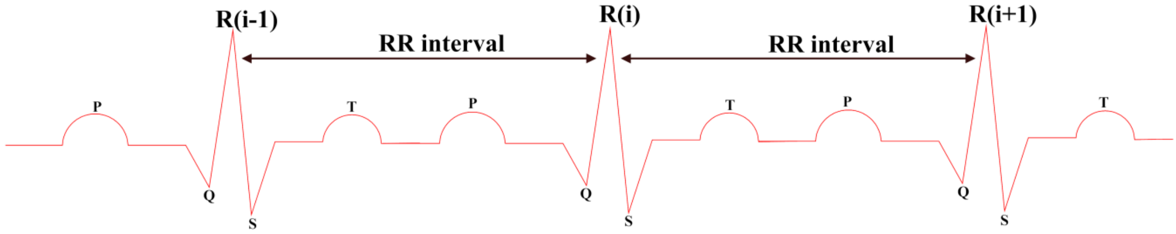

Figure 4. RR interval between two consecutive R peaks in the ECG signal (Yakut et al. 2014)

Four features were extracted using the RR intervals. These; the pre-RR interval was the RR interval between a given heartbeat and the previous heartbeat. The post-RR interval was the RR interval between a given heartbeat and the next heartbeat. The average RR interval was the average of the RR intervals for a record and had the same value for all heartbeats in a record. Finally, the local average RR interval was determined by taking the average of ten RR intervals (5 RR intervals before RR (i), 5 RR intervals after RR (i)) surrounding a heartbeat (Chazal et al. 2004; Chazal, 2013; Yakut, 2018).

P wave, QRS complex, T wave, the segments and the intervals in the ECG signal were separated into time windows as shown in Figure 3 to obtain the fiducial points in the signal. The 256 sample segments were divided into time windows according to the components of the ECG signal. Then, morphological features were extracted from the ECG signal using these points (Yakut, 2018).

2.4. Feature Selection

The SelectKBest (SelectKBest, 2020) method scores the given feature set using the f_classif score function. SelectKBest method calculates the importance levels of the features according to the score function used. It then sorts the features according to their severity starting with the best and returns a list or array of results.

In Figure 5, the order of the features obtained as a result of the feature selection process is given according to their severity level. In this study, the severity levels of the ECG morphology-based extracted features were obtained to determine the most significant features by using the SelectKBest method and f_classif score function. When these severity levels are listed from highest to lowest, 20 features are determined as shown in Figure 5. In Figure 5, the names of the features selected on the x-axis and the severity levels of the selected features on the y-axis are included. Features in Figure 5 have been selected based on the features whose importance is over 1000.

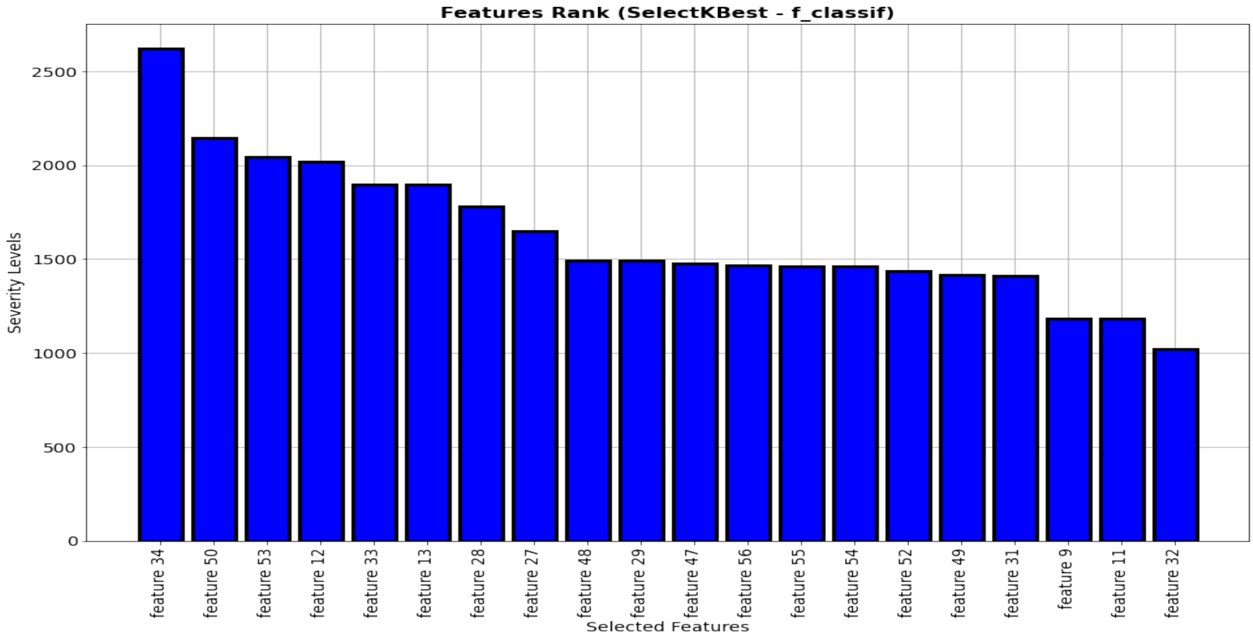

Figure 5. Selecting 20 ECG morphology-based features with the SelectKBest method

2.5. Machine Learning Methods

In this study, Scikit-learn (Scikit-learn, 2020) machine learning library was used. Machine learning methods such as SelectKBest, Logistic Regression (LR), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) and Multi Layer Perceptron (MLP) were used in the study. SelectKBest feature selection method was used for feature selection. These methods were developed using the Python programming language. Each machine learning method has its own hyperparameters. In this study, the hyperparameters of the methods used were run using the default values in Scikit-learn machine learning library. Thus, machine learning methods worked according to the principles required by their own algorithms. Then, when these methods were desired to be operated for the same purpose at different times, it was ensured that similar results were obtained under the same conditions with the same hyperparameters.

3. EXPERIMENTAL STUDY

In this study, an arrhythmia detection method is proposed whose block diagram is shown in Figure 6. First, the ECG signal is cleared of baseline wander noise. Then, the positions of the R peaks in the ECG signal were obtained by using the annotation file in MIT-BIH AD. Using this location information, a window containing 127 samples before the R peak and 128 samples after the R peak of the ECG signal was created. Thus, 57 morphology-based features were extracted from the ECG signal using this window. The extracted features were brought to the range [0,1] using the min-max normalization technique. Then, the SelectKBest method was used together with the f_classif score function in order to select the most meaningful of the extracted features. Thus, the SelectKBest method ranked the extracted features according to their significance. Thus, the 20 most significant ECG morphology-based features were selected. In this study, both the data set containing 57 features and the data set containing 20 features were used for classification. Heartbeats in these data sets were distributed as training and test data set as shown in Table 1. These data sets fed LR, LDA, MLP and SVM classifiers using the five-fold cross-validation technique. Classification performance results of machine learning methods were obtained. The most successful method was determined by comparing the performance results with each other. As a result, the most successful method has been compared with other studies in the literature. Thus, a method for predicting five basic arrhythmias has been proposed.

This study was developed in Python programming language and Scikit-learn (Scikit-learn, 2020) machine learning library was used. At the same time, the Google Colaboratory (Google Colaboratory, 2020) environment which uses the Google Cloud Computing infrastructure was used for the software and hardware needed by machine learning algorithms. In this study, Matlab R2015b (The MathWorks, Inc., Natick, MA, USA) software was used to clear the noise in the ECG signal and extract the ECG morphology-based features.

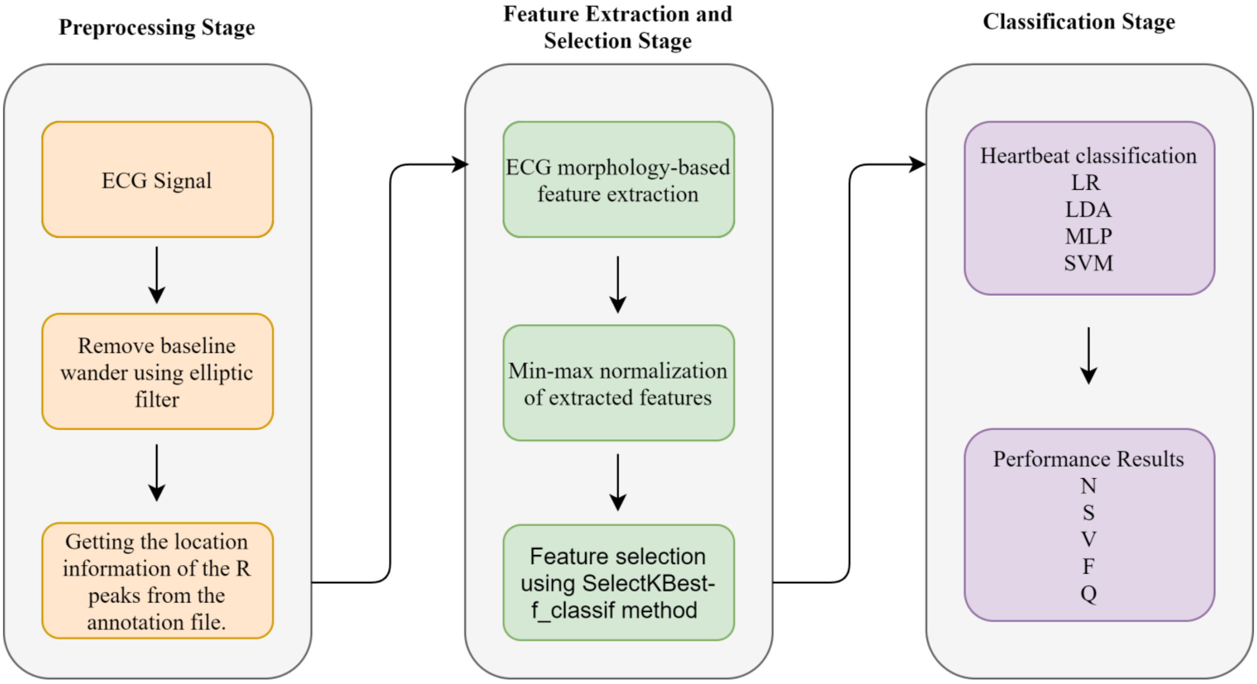

Figure 6. Block diagram of the proposed arrhythmia detection method

4. EXPERIMENTAL RESULTS

Table 3: Performance results of 57 features based on ECG morphology

Methods		Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
Logistic Regression	Training	99.300	98.570	99.031	98.800
	Testing	**99.801**	99.503	99.876	99.503
Linear Discriminant Analysis	Training	98.698	98.423	99.121	98.770
	Testing	99.339	98.346	99.587	98.963
Support Vector Machine	Training	96.840	96.500	97.770	97.130
	Testing	98.806	97.015	99.254	98.122
Multi Layer Perceptron	Training	97.185	97.200	98.910	98.050
	Testing	98.623	96.557	99.139	97.831

In this study, firstly, the ECG morphology-based features consisting of 57 features were classified using machine learning methods. This data set consisting of 57 features was divided into two as training and testing. The training data set contained 51527 heartbeats. The test data set included 49825 heartbeats. LR, LDA, SVM and MLP machine learning methods were fed by these two data sets. The performance results of machine learning methods are shown in Table 3.

The ROC AUC (Area Under the Receiver Operating Characteristic (ROC) Curve) graph of machine learning methods that diagnose arrhythmia using 57 features based on ECG morphology was obtained. In Figure 7, the arrhythmia detection performance of machine learning methods is compared.

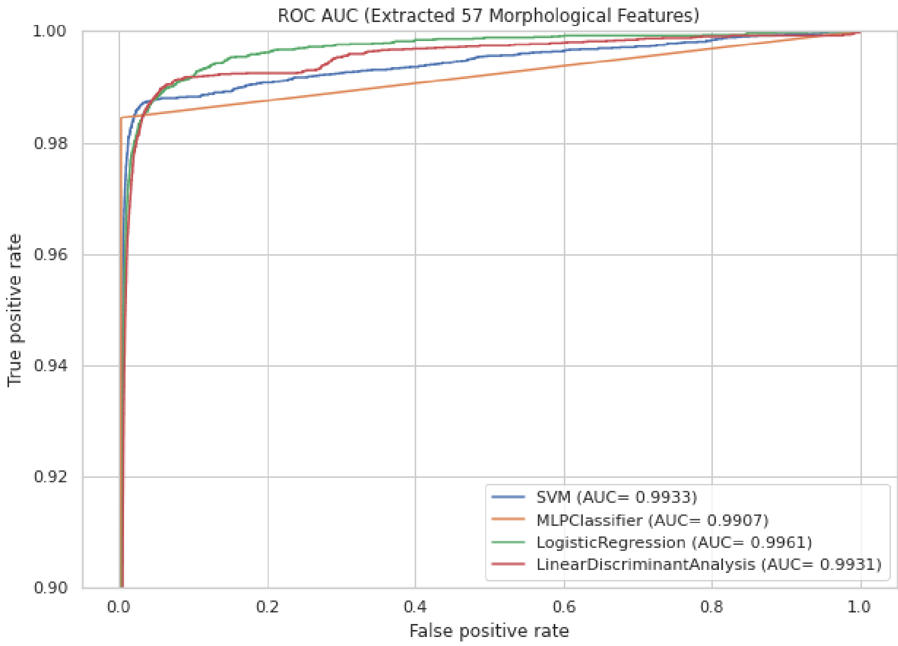

Figure 7. ROC AUC graph of machine learning methods (57 features)

In this study, five basic arrhythmias were classified using machine learning methods utilizing ECG morphology-based features consisting of 20 selected features. The data set consisting of 20 selected features was divided into two as training and testing. The training data set contained 51527 heartbeats. The test data set included 49825 heartbeats. LR, LDA, SVM and MLP machine learning methods were fed by these two data sets. The performance results of machine learning methods are shown in Table 4.

Table 4: Performance results of 20 selected features based on ECG morphology

Methods		Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
Logistic Regression	Training	99.272	98.985	99.147	99.066
	Testing	**99.766**	99.416	99.854	99.416
Linear Discriminant Analysis	Training	99.054	98.939	99.026	98.982
	Testing	99.697	99.243	99.811	99.243
Support Vector Machine	Training	98.214	97.998	98.101	98.049
	Testing	99.552	98.880	99.720	99.298
Multi Layer Perceptron	Training	97.142	97.125	98.745	97.930
	Testing	98.776	96.939	99.235	98.074

The ROC AUC graph shown in Figure 8 of machine learning methods that diagnose arrhythmia using selected 20 features based on ECG morphology was obtained. In Figure 8, the arrhythmia detection performance of machine learning methods is compared.

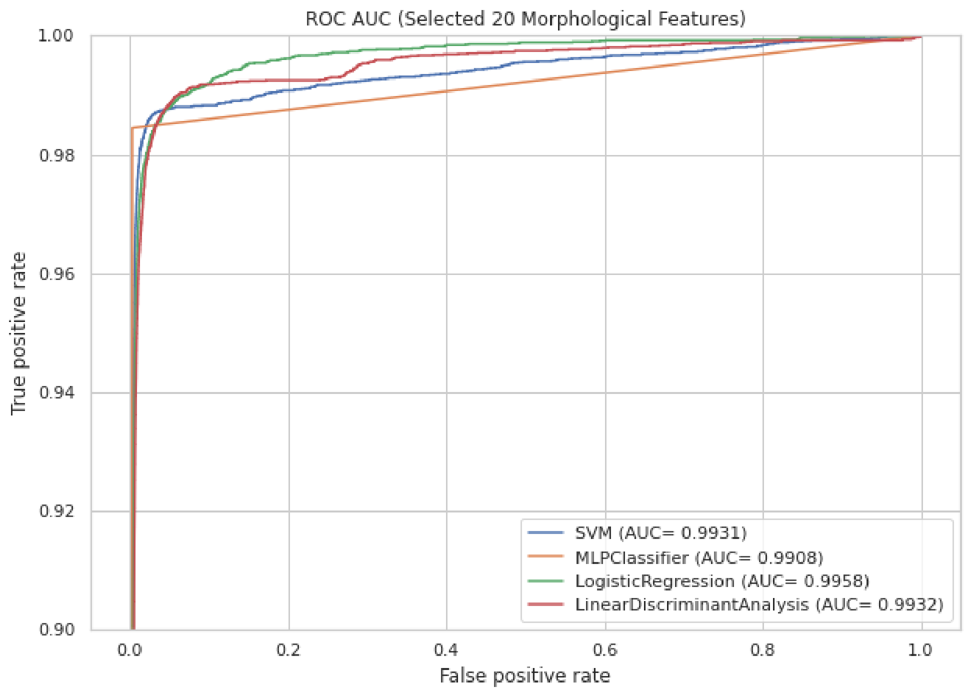

Figure 8. ROC AUC graph of machine learning methods (selected 20 features)

5. DISCUSSION

In Table 3, arrhythmia diagnosis results made with 57 morphology-based features are listed from high performance to low success. The performance results of the LR method are Accuracy 99.801%, Sensitivity 99.503%, Specificity 99.876% and F1-Score 99.503%. The performance results of the LDA method are Accuracy 99.339%, Sensitivity 98.346%, Specificity 99.587% and F1-Score 98.963%. The performance results of the SVM method are Accuracy 98.806%, Sensitivity 97.015%, Specificity 99.254% and F1-Score 98.122%. The performance results of the MLP method are Accuracy 98.623%, Sensitivity 96.557%, Specificity 99.139% and F1-Score 97.831%. It has been found that machine learning methods produced similar results when compared with each other. The results of the machine learning methods in this study were found to have sufficiently high accuracy for arrhythmia diagnosis. Among the machine learning methods in this study, it was observed that the most successful arrhythmia diagnosis made with 57 morphologically based features belonged to the LR method.

In Table 4, arrhythmia diagnosis results made with 20 selected morphologically based features are listed from high performance to low success. The performance results of the LR method are Accuracy 99.766%, Sensitivity 99.416%, Specificity 99.854% and F1-Score 99.416%. The performance results of the LDA method are Accuracy 99.697%, Sensitivity 98.243%, Specificity 99.026% and F1-Score 98.982%. The performance results of the SVM method are Accuracy 99.552%, Sensitivity 98.880%, Specificity 99.720% and F1-Score 98.298%. The performance results of the MLP method are Accuracy 98.776%, Sensitivity 96.939%, Specificity 99.235% and F1-Score 98.074%. Comparing the performance of machine learning methods with each other close results were obtained. The performance results of the machine learning methods in this study have sufficiently high accuracy for the diagnosis of arrhythmia. As a result of arrhythmia diagnosis made with 20 morphologically based features, the LR method was observed to be the most successful among machine learning methods in this study.

The ROC AUC results show how well predictive machine learning methods. It is a criterion that is accepted as a summary of the performance of the machine learning methods used. It also allows these methods to be compared better with each other. The greater the area covered by ROC AUC, the more effective machine learning methods are in distinguishing arrhythmia classes.

When Figure 7 and 8 are examined, the AUC values of LR, LDA, SVM and MLP methods were found to be quite high. Thus, it was concluded that the machine learning methods developed were able to detect arrhythmia perfectly well.

When the machine learning methods in Figure 7 are examined, the AUC values were provided as 99.61% for LR, 99.31% for LDA, 99.33% for SVM and 99.07% for MLP from high to low lower success. The results obtained are very close to each other and at the same time satisfactorily high values.

When the machine learning methods are examined in the graphic in Figure 8, the AUC values were provided as 99.58% for LR, 99.32% for LDA, 99.31% for SVM and 99.08% for MLP from high to low success. The results obtained are very close to each other and at the same time satisfactorily high values.

In this study, the results of arrhythmia detection using 20 features obtained as a result of the feature selection process are almost the same as the data set with 57 features. Thus, by reducing the size of the data set, the computational complexity and the load of machine learning methods have been reduced. At the same time, the performance of machine learning methods did not decline and remained the same. It builds confidence in the medical use of the proposed arrhythmia diagnostic method. It also facilitated the implementation of the proposed arrhythmia diagnosis method. Thus, the proposed method will need less system resources.

When the machine learning methods in Figures 7 and 8 are examined, the machine learning method with the highest success is the Logistic Regression (LR) method. In this study, this method has been proposed to classify arrhythmia. The results of this method are compared with other studies in literature in Table 5.

Table 5. Comparison of the proposed method with other studies in the literature

Study	Feature Extarction Technigue	Classifier Method	Class	Accuracy (%)
This Study	ECG Morphology-Based Features	LR	5	99.76
Raj, 2020	DDCWT	ABC+SVM	5	97.20
Martis et al. , 2013	PCA	LS-SVM	5	93.48
Jiang and Seong, 2007	Hermite Function Params & RR Interval	Block-Based NN	5	96.60
Chazal and Reilly, 2006	Morphology & Heartbeat Interval	LDA	5	85.90

When the performance results they obtained to diagnose the five basic arrhythmias of the studies in Table 5 are examined, it is concluded that the method proposed in this study has a higher accuracy value. Thus, it shows that the proposed method has the ability to detect arrhythmia quite usefully.

Since the proposed method uses the morphological features of the ECG signal, it can better adapt the changes in the ECG signal, providing more successful results in arrhythmia prediction. Thus, when the performance results of the proposed method are examined, it stands out from other methods in the literature. At the same time, the proposed method will consume even less system resources as the size of the feature dataset is reduced. Thus, the computational load of the proposed method is low. The proposed method has presented an arrhythmia diagnosis system with a low computational load and high performance, using features of ECG morphology to the literature.

6. CONCLUSION

In this study, an IIR based elliptic digital filter that removes the baseline wander in the ECG signal is used. Morphologically based features of the ECG signal were extracted. Then, the most meaningful morphological features were selected among these features. According to the AAMI standard, five basic arrhythmiaswere classified using machine learning methods using these features. When the obtained results were examined, the Logistic Regression method which predicted the five basic arrhythmias as satisfactorily high was proposed. The proposed method has presented an arrhythmia diagnosis system with a low computational load and high performance using features of ECG morphology to the literature. Thus, the proposed method can be used for automatic classification of heartbeats with arrhythmias in computer-aided diagnosis systems. In future studies, different ECG data sets containing heartbeats with arrhythmias can be used. At the same time, results can be further improved by using more advanced machine learning methods.

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