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12-Lead ECG Signal Analysis for Myocardial Infarction Diagnosis: Empirical Mode Decomposition and Machine Learning Application

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Abstract: - The characteristic changes in electrocardiogram (ECG) signals can be complex and difficult to monitor. If these changes are recognized early, heart diseases such as myocardial infarction (MI) can be prevented. The development of artificial intelligence-based systems can provide early diagnosis of these diseases and help cardiologists in diagnosis. This paper presents an empirical mode decomposition (EMD)-machine learning-based approach for the early diagnosis and classification of STEMI and NSTEMI. The 12-lead ECG signals obtained from two different datasets with similar characteristics are analyzed and the signals are decomposed into their principal components using the EMD method. Features are extracted from the decomposed signals and the ones that are significant for the performance of the classifier model are determined by Least Absolute Shrinkage and Selection Operator (LASSO). Healthy controls (HC), NSTEMI, and STEMI groups were classified using SVM and ANN algorithms. The most successful results in the classification process were obtained with the SVM algorithm. The classification of the HC-NSTEMI group was 99.84%, the HC-STEMI group was 99.90%, and the HC-STEMI-NSTEMI group was 99.70% Area Under Curve (AUC). The findings obtained in the study may contribute to the development of systems to support the early diagnosis of cardiac abnormalities such as MI and may give cardiologists the opportunity for early intervention in heart diseases.

Keywords: Electrocardiogram signal, Empirical mode decomposition, Machine learning, Myocardial infarction.

I. Introduction

Coronary heart disease is the leading cause of death in the world [1]. The main cause of this disease is damage to the coronary vasculature. Myocardial Infarction (MI), also known as heart attack, is one of the types of this condition, also known as acute coronary syndrome, with the highest risk of death [2]. MI is a condition in which the heart muscle becomes oxygen deficient as a result of occlusion of the coronary artery [3]. The primary diagnostic tool for MI is the non-invasive 12-lead electrocardiogram (ECG) [4]. In clinical settings, a 12-lead ECG can provide more valuable information than a single lead [5]. MI is divided into Non-ST-elevation-MI (NSTEMI) and ST-elevation-MI (STEMI) according to the wave changes in ECG signals (whether or not there is elevation in the ST segment) [4]. These characteristic changes in ECG signal waves are complex to monitor and analyze manually. In some cases, there may be undetectable ST segments in the ECG signal. The identification of these conditions and the discrimination of NSTEMI-STEMI can be difficult for cardiologists [6, 7]. To overcome this difficulty, studies on the development of computer-aided diagnostic systems that can provide automatic diagnosis are ongoing [8, 9]. These systems, which can provide automatic diagnosis of MI and its types, are based on artificial intelligence and are effective and computationally efficient [9].

Machine learning algorithms and deep learning algorithms from artificial intelligence techniques are generally used in research [10, 11]. However, to train neural networks in deep learning methods, the sample size in the dataset must be large [12]. In this case, the small number of samples may be a limitation for applying deep learning methods in research [11]. For this reason, machine learning algorithms based on feature engineering are preferred in most studies [10]. The processing of ECG signals is important in the automatic diagnosis and classification of cardiovascular disorders such as MI [13]. By analyzing the features extracted from ECG signals with machine learning algorithms, MI can be classified into categories. Therefore, the performance of the MI diagnosis and classification model depends on the extraction of distinctive features that characterize the ECG signal [10, 14]. In many studies, features have been extracted from the frequency domain by applying wavelet transform-based methods to ECG signals for MI detection. However, these methods may be disadvantageous since choosing basis functions is important [15]. In order to extract dominant and distinctive features from ECG signals, methods such as empirical mode decomposition (EMD), variational mode decomposition (VMD), local

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mean decomposition (LMD), and tunable-Q wavelet transform (TQWT) can be more effective [14]. Since ECG signals are non-stationary and random, they can be analyzed more easily with methods that can decompose signals into modes [14, 16, 17]. There are MI detection techniques developed based on signal processing and machine learning by applying these methods to ECG signals [18]. Recent research on MI detection based on machine learning by applying signal processing methods to 12-leadECG signals is described in the next paragraph.

In their study, Zeng et al. presented a new pattern recognition-based method for MI detection. They extracted representative features from 12-lead ECG signals obtained from 290 participants using TQWT, VMD, and Phase Space Reconstruction methods. With these features, classification was performed using the RBF Neural Networks model and 10-fold cross-validation technique [18]. Acharya et al. preferred the K-Nearest Neighbour (KNN) classifier by extracting 9 features from ECG signals with the EMD technique in their study for automatic detection of MI [19]. In another study on MI detection using the VMD method, mode energy, and covariance matrices were used as multiscale features. KNN and SVM algorithms were preferred in the classification process [20]. Sahu and Ray proposed a new technique for MI detection and localization in their research. In their proposed technique, the features obtained by using VMD and regularised neighborhood component analysis methods were evaluated with the KNN algorithm [21]. A detailed comparison of the results of these studies and similar studies in the literature with the results obtained in our study is given in Section 4.

In the present study, 12-lead ECG signals for MI detection are analysed by applying the EMD technique. Since the EMD method can separate the basic oscillation modes of the ECG signal from the original signal, it can solve the constant window problem arising in methods such as Fourier transform or discrete wavelet transform, and it can provide orthogonality advantage thanks to the signal internal mode functions [21, 22]. As a result of the analyses, some of the basic signal features were obtained from ECG signals, and HC-NSTEMI, HC-STEMI, and HC-STEMI-NSTEMI groups were classified by machine learning methods. In most of the studies on MI detection, MI-HC groups are classified as binary groups [15, 18, 20]. In this study, to distinguish the most common and complex types of MI (NSTEMI-STEMI) from healthy control groups, the classification process was performed as binary groups and triple groups. We believe that the classification results obtained in this study have high evaluation criterion rates for the detection of MI and the determination of its types. In the rest of the research, the methodology, dataset, and applied method-algorithms are mentioned in section 2. In section 3, the research results are presented and discussed. In the last section, the research and its results are summarised and explained.

II. Methods

The methodology of the proposed work can be summarised in three steps. Acquisition of ECG signals, signal preprocessing, feature extraction, and classification steps. In the first step of the research, 12-lead ECG signal records obtained from 2 different datasets (database and our records) were analyzed. In the second step, signal preprocessing, feature extraction, and feature selection processes were performed. Filtering operations were performed to remove the noise of ECG signals. The filtered signals were decomposed into IMFs by applying EMD. Basic signal features were obtained from the EMD-applied ECG signals and the features that would positively affect the performance of the classifiers were selected by the Least Absolute Shrinkage and Selection Operator (LASSO) method. In the last step, the classification of HC-NSTEMI, HC-STEMI, and HC-STEMI-NSTEMI groups was performed with ANN, and SVM algorithms, and the performance evaluation was analyzed by obtaining criterion rates. The flowchart summarising the study is given in Fig.1.

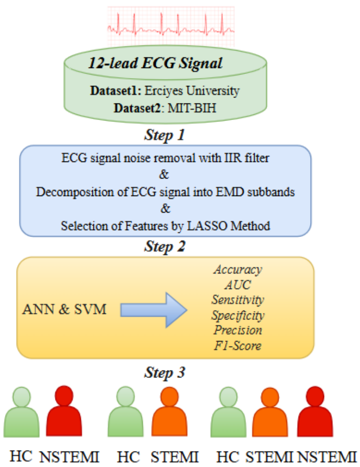

Fig. 1. Flowchart summarising the methodology of the proposed study

A. Dataset

In this study, two different data sets, our records and open source, were used. The common feature of the data sets used is that they have 12-lead ECG signals. Dataset 1 consists of 12-lead ECG signals of people who came to Erciyes University Hospital Emergency Department with chest pain between 2018-2023 (approval number: 2022/536). These signals consist of healthy control, STEMI and NSTEMI diagnosed participants. In each group, 128 ECG recordings of 10 seconds each were analysed. Dataset 2 was obtained from ECG signals in the 'MIT-BIH' database shared as open source on PhysioNet [22]. The number of participants and the signal length of the ECG signals obtained from this database were adjusted to be the same as our recordings.

B. Pre-processing of ECG signals

In the raw form of ECG signals, there may be noise due to the influence of different signals and the environment. These noises need to be removed before analysing. In the signal pre-processing step, low and high-frequency noises in ECG signals are removed by designing an IIR low-pass filter with a cut-off frequency of 2-40 Hz. The noise-removed ECG signals were normalised with z-score and the signal processing step was started. In the signal processing step, the EMD technique was applied to decompose the ECG signals into sub-modes. The EMD method does not leave the time domain by obtaining the basic functions directly from the original signal. With this feature, it provides an advantage over some techniques applied in studies [21, 23]. In the EMD method, the instantaneous information of the Intrinsic Mode Functions called IMF is obtained by Hilbert transform [21]. With the EMD method, the frequencies of the original signal are reduced and divided into IMF components. During the creation of IMF components, local maxima, and minima are first obtained from the signal. Then, envelopes are obtained by combining all the maxima and minima obtained. IMFs of a signal are created by averaging these envelopes. After testing whether the generated IMFs fulfil the conditions, these processes are repeated until it is realized that no more IMFs can be obtained [19, 24]. In the present study, experiments were conducted with reference to the stopping criterion and ECG signals were decomposed into intrinsic mode functions. Sample ECG signals decomposed into sub-modes by the EMD method are given in Fig. 2.

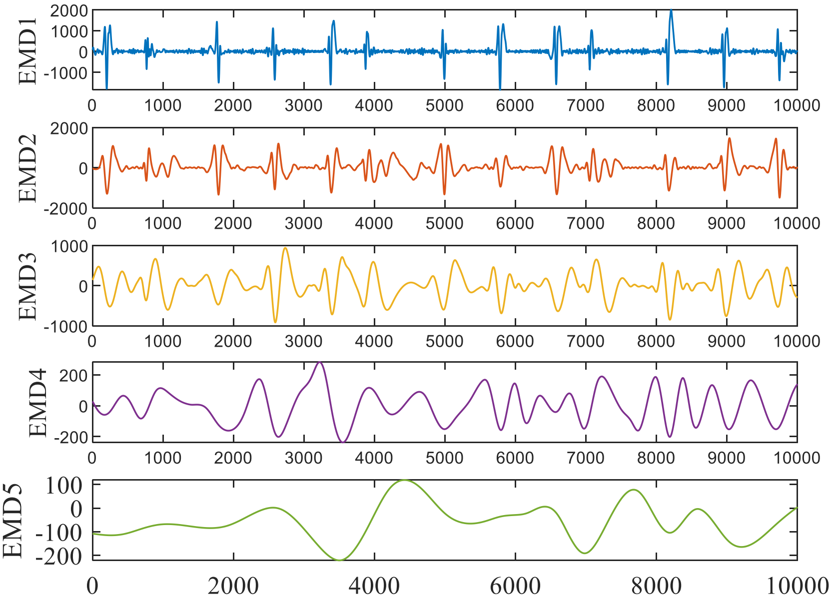

Fig. 2. Sample ECG signal decomposed into intrinsic mode functions by EMD

C. Feature Extraction and Selection

Before the classification step, it is important to obtain some features to define the dataset correctly and to perform the classification process easily. In this study, some basic signal features such as Skewness, Kurtosis, Variance, Average Energy, Mean of Absolute Differences, Shannon Entropy, Renyi Entropy were obtained from EMD applied ECG signals (12-lead x 5 IMF x 15 Features). LASSO was applied to determine the features that can positively affect the classifier's performance. The LASSO method is applied to minimize the error between the observed and predicted values by providing a low variance estimate [25]. When LASSO is applied for the feature selection process, the choice of lambda (λ), which is the regularisation parameter, is important. In this study, different λ parameter values were tested and 0.0001 was selected as the most appropriate value according to the prediction error.

D. Classification Process and Performance Evaluation

The purpose of the classification process is to accurately predict the data labels applied as input to the classifier algorithms. Different machine-learning algorithms are used in this process. In this research, ANN and SVM algorithms were preferred and classification processes were performed. The Machine Learning Toolbox of MATLAB R2023b was used for these operations. While performing the classification processes, a 10-fold cross-validation (CV) technique was applied in the training and testing phase of the data. From the data applied as input to the classifiers, 10% of the data were randomly separated for testing and 90% for training, and the classification process was performed. These steps were repeated 10 times and average performance evaluation criterion rates were obtained. In this study, Area Under Curve (AUC), Accuracy (Acc), Sensitivity (Ss), Specificity (Sp), Precision (Pr), and $F1$-Score (F1) were obtained as performance evaluation criteria rates. True positive (tp), true negative (tn), false positive (fp), and false negative (fn) values in the confusion matrix are used to obtain these rates [26].

III. Result And Discussion

In this study, aims to differentiate NSTEMI-STEMI, one of the types of MI that can be difficult to detect manually by physicians and can cause complexity, from healthy control groups. For this purpose, a model based on machine learning algorithms and EMD technique is presented. In the presented model, ECG signals are decomposed into subcomponents with the EMD technique, and some of the preferred signal features are obtained. From these features, the ones that can positively affect the classifier performance are selected with LASSO, and the classification process is performed with ANN and SVM algorithms. While performing this process, HC-NSTEMI, HC-STEMI groups as a binary class, and HC-STEMI-NSTEMI as a triple class were analyzed. Our own clinical data (Dataset1) and open-source (Dataset2) 12-lead ECG signals were used in the analysis. The classification process was performed 5 times and the average rates of the performance parameters are given in Tables 1-3, respectively.

When Tables 1-3 are examined, it is seen that both of the machine learning algorithms preferred in the study give close and successful results. However, the most successful algorithm was SVM. Each of the performance criterion rates is important in the evaluation of model performance in classification processes and expresses different situations. However, AUC and accuracy rates are mostly emphasized in the studies and it is stated that they provide important information [27, 28]. From a medical point of view, it has been stated that the AUC rates is more informative than the accuracy rate [26]. When the AUC rate is close to 100%, the classifier performance is interpreted as close to perfect [28]. According to this information, when evaluated in terms of AUC rates, the most successful result in the classification of the HC-NSTEMI group was obtained in the SVM algorithm with 94.73% in the data we collected and 99.84% in the MIT-BIH dataset. In the classification of the HC-STEMI group, AUC rates of 97.54% with Dataset1 and 99.90% with Dataset2 were obtained. Accuracy rate and other metric rates also showed very successful performance in the classification of binary groups. In the classification of the HC-STEMI-NSTEMI group, AUC rates of 99.70% in Dataset1 and 99.69% in Dataset2 were obtained. In the classification of this group, successful results were obtained in other criteria rates. However, the accuracy rate remained slightly low. While the model proposed in this study can classify binary groups very well, it should be improved a little more in the classification of triple groups. We think that the reason for the low accuracy rate in the classification of the triple group is that the distinction between STEMI and NSTEMI, which are close to each other according to the ECG wave change, cannot be made very well. This rate can be increased with systems that can be developed in the future.

When the recent studies on MI detection using machine learning are examined, it is seen that they are generally on feature extraction from ECG signals [15]. VMD, EMD, and similar signal decomposition techniques are used to extract these features. In this way, signals are easily analyzed and important information is preserved [16, 29].In a study using the EMD technique and 12-lead ECG signal, nine features were obtained MI-HC groups were classified by the KNN classifier and an 81.84% accuracy rate was obtained [19]. In studies using the VMD technique, some features were obtained from 12-lead ECG signals, and a 97.98% accuracy rate was obtained with RBF neural networks [18], a 99.86% accuracy rate in SVM algorithm [20], and a 99.82% accuracy rate in KNN algorithm [20]. The VMD technique is considered to be a more advantageous method that has been introduced to the literature to improve the EMD technique [18]. When the results of the studies in the literature are examined, the superiority of the VMD technique is seen. However, it is seen that the results obtained in this study are close to the results obtained with VMD in the literature and superior to the studies conducted with the EMD technique. In this study, we think that determining the best feature set by applying the feature selection method (LASSO) while applying EMD improves the model performance.

Although the classification of MI types has not received much attention, it is evident from the studies discussed above and in the literature that cardiac problems or MI are on the differentiation of MI from HC groups [18, 30]. In this study, we think that it is important to classify MI types into three groups from HC groups. The fact that the model proposed in this study was analysed with two different datasets with similar characteristics is one of the important situations in terms of non-randomness and healthier interpretation of the results. It is important to decompose non-stationary signals such as ECG into local components or subbands for easier analysis [17, 31]. EMD is one of the suitable methods for decomposing these signals and is widely used in research [24, 31]. One of the advantages of the EMD method is that by removing high-frequency components, it can preserve useful information in the ECG signal and provide appropriate features [29]. In addition, the EMD method is advantageous in terms of processing 12-lead ECG signals simultaneously while decomposing them [30]. For this reason, the choice of EMD technique in this study is another important point for the study. It is also important to analyse 12-lead ECG signals in this study. Because, although successful results have been obtained in studies with single-lead ECG signals in the literature, 12-lead ECG signals can provide more realistic information in clinical settings. Although the study has positive and important points, it also has some disadvantages. The fact that it was analysed only with the EMD technique and the sample size was relatively low may prevent a healthy interpretation of the results. Although analysing the HC-STEMI-NSTEMI groups in triplicate is positive considering the literature studies, the low accuracy rate is a negative situation. In the future, the applied model can be improved by increasing the number of samples with different techniques and different features.

Table I. HC-NSTEMI classification performance rates

	Dataset1(Clinical)		Dataset2 (“MIT-BIH”)	
	ANN	**SVM**	**ANN**	**SVM**
AUC (%)	93.80	94.73	99.81	99.84
Acc. (%)	86.25	87.10	98.75	98.82
Ss. (%)	85.00	85.32	98.12	98.28
Sp. (%)	87.50	88.75	99.37	99.38
Pr. (%)	87.21	88.35	99.37	99.37
F1 (%)	86.10	86.79	98.74	98.82

Table IIIII. HC-STEMI classification performance rates

	Dataset1(Clinical)		Dataset2 (“MIT-BIH”)	
	ANN	**SVM**	**ANN**	**SVM**
AUC (%)	97.35	97.54	99.90	99.90
Acc. (%)	92.73	92.81	99.29	99.76
Ss. (%)	93.90	93.13	98.75	99.68
Sp. (%)	91.56	92.50	99.84	99.84
Pr. (%)	91.75	92.56	99.84	99.84
F1 (%)	92.81	92.84	99.29	99.76

Table IVVVI. HC-STEMI-NSTEMI classification performance rates

	Dataset1(Clinical)		Dataset2 (“MIT-BIH”)	
	ANN	**SVM**	**ANN**	**SVM**
AUC (%)	99.50	99.70	99.53	99.69
Acc. (%)	79.70	79.60	79.73	79.63
Ss. (%)	98.60	97.30	98.59	97.34
Sp. (%)	97.70	98.50	97.65	98.51
Pr. (%)	95.50	97.10	95.48	97.10
F1 (%)	97.00	97.20	97.00	97.19

IV. Conclusions

In this study, 12-lead ECG signals of NSTEMI and STEMI participants from the HC group and MI types were analysed and classified with a model based on machine learning algorithms and EMD technique. ANN and SVM algorithms were used in the classification processes performed as HC-NSTEMI, HC-STEMI, and HC-STEMI-NSTEMI. In order to interpret the performance of the model more accurately, two different data sets with similar characteristics were used. When the performance evaluation criterion rates of the model are analyzed, both algorithms have obtained similar and successful results for the two data sets. These results may contribute to the development of systems that can provide early diagnosis of cardiac abnormalities such as MI, which can be difficult for cardiologists to detect. In this way, the time required for diagnosis can be reduced and early treatment can be started.

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Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

Ethical approval for the conduct of the study was obtained from Erciyes University Clinical Research Ethics Committee (decision no: 2022/536).

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