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Research Article

Alternative Approach to Investigation of Cardiovascular Diseases: Analysis of ECG Signal with Robust Local Mean Decomposition

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ABSTRACT

According to the World Health Organization, cardiovascular diseases (CVDs) are the group of diseases that cause the most deaths worldwide. Among the types of CVD, myocardial infarction (MI) stands out as the most researched and difficult to diagnose by clinicians. MI is divided into two subgroups ST-elevation-MI (STEMI) and Non-ST-elevation (NSTEMI) depending on the ST segment in the Electrocardiogram (ECG) signals. Early diagnosis of these diseases importance in terms of reducing the risk of death. This study aims to develop a system that automatically analyzes ECG signals belonging to CVDs, which can be difficult for clinicians to analyze manually. In this study, signal processing was performed using the Robust Local Mean Decomposition (RLMD) method, and feature selection was performed using the LASSO and Chi-square methods. Random Forest (RF) and Support Vector Machines (SVM) algorithms were used for classification. The classification process was performed among CVDs (three groups) and by including healthy control data (four groups). The results were evaluated with accuracy, Area Under the Curve (AUC), and negative predictive value (NPV) criterion rates. The findings obtained showed that the RF algorithm was slightly superior to SVM in classification performance. Similarly, the LASSO method achieved more successful results in feature selection. It was observed that the AUC and NPV rates were over 84% for the groups examined in two different classifiers and feature selection methods. This situation proves that the proposed method is a stable and reliable analysis tool. This research draws attention as one of the limited number of studies using the RLMD method in the analysis of ECG signals and the diagnosis of CVD. The presented study can contribute to the development of systems that can overcome the difficulties experienced in manual analysis, especially in the diagnosis of CVDs and to support physicians in clinical processes.

Keywords: Cardiovascular diseases, Electrocardiogram, Robust Local Mean Decomposition, LASSO, Random Forest.

INTRODUCTION

According to World Health Organization research, heart diseases are the leading cause of death worldwide [1]. Heart diseases are known as Cardiovascular diseases and have been an interesting topic for researchers for years [2]. CVDs may occur as a result of damage to the coronary vasculature due to diet, lifestyle, stress, physical activity, blood pressure, etc. [2, 3]. There are different types of CVDs. The most common of these are cerebrovascular disease, coronary heart disease, cardiomyopathy, myocarditis, and MI. The highest mortality risk of these diseases MI [4]. MI is divided into NSTEMI and STEMI according to the change in the ST segment in the ECG signal [5]. Early diagnosis of these diseases and rapid initiation of treatment is important. The imaging method widely used clinically in the diagnosis of CVDs is the 12-lead ECG [2, 6]. ECG is a non-invasive method and presents the electrical activity of the

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heart graphically to clinicians. However, the differences in cardiac graphs, especially in patients with MI, can be difficult and time-consuming to analyze manually in some cases. Computer-aided automated diagnostic systems are needed for easy analysis of CVDs.

Artificial intelligence-based algorithms are at the center of computer-aided automatic diagnosis systems. The basic structure of these systems consists of the preprocessing of ECG signals, feature extraction and selection of important features, and classification [7]. Such systems have high accuracy of diagnosis and computational efficiency [8]. In recent studies, it has been seen that deep learning algorithms are widely preferred in the classification stage. However, the number of data is expected to be sufficient for deep learning algorithms to work and train efficiently. For this reason, machine learning algorithms are preferred when the number of data is relatively low [9, 10]. In machine learning algorithms, before the classification process, features should be extracted from ECG signals and important features should be identified. In recent studies, different signal processing methods have been applied for this stage. Due to the structure of ECG signals, adaptive decomposition algorithms that separate the signals into different subbands have been preferred to extract the most effective features from the frequency and time domain [11, 12]. Adaptive signal processing methods such as Empirical mode decomposition (EMD), Discrete wavelet transform (DWT), and Variational mode decomposition (VMD) have been used more than these algorithms in studies on cardiac disorders [12, 13]. In the signal decomposition stage of these methods, some disadvantages may arise in determining the boundary effect. RLMD method can overcome these disadvantages and is more attractive than EMD, VMD, and DWT methods [13-15]. For this reason, in this study, the RLMD method and machine learning algorithms SVM and RF were preferred and CVDs were analyzed. Many studies have analyzed CVDs using EMD, VMD, etc. methods. RLMD method has been applied in different fields and the analysis of biomedical signals [15-17]. However, to the best of our knowledge, there are very few studies on the analysis of ECG signals [18]. In this research, 12-lead ECG signals were analyzed with RLMD technique and machine learning algorithms to contribute to the development of systems that can identify the type of CVDs and distinguish CVDs from healthy control groups. The aim and main contributions of this research are summarised below.

1. This study aims to contribute to the development of systems that can perform automatic analysis and classification of ECG signals of CVDs, which can be difficult for clinicians to analyze manually. In this context, ECG signals of STEMI and NSTEMI, which are the most common and confused types of MI, and other cardiac patients were analyzed rather than only a single type of heart disease.

2. In this study, the RLMD method was preferred, unlike the studies in the literature. Some studies perform CVD analysis with methods such as EMD, VMD, etc., which have a similar working logic to the RLMD method. However, the RLMD method can be considered new for the literature and there is almost no research on the analysis of ECG signals.

3. In this study, LASSO and Chi-square feature selection methods, which are widely preferred in the feature selection phase, were preferred. In this way, the importance of feature selection was investigated and the performance of the methods was compared.

4. In the classification phase of the study, RF and SVM machine learning algorithms with different working principles were preferred instead of a single machine learning method. In this way, the non-randomness and stability of the results are emphasized.

METHODS

This study includes both the classification of CVDs among themselves and their differentiation from healthy control groups. For this purpose, ECG signal records were collected from the clinic in the first stage. ECG signals were decomposed into subbands by the RLMD method by removing noise and preprocessing stages. Entropy and statistical features were obtained from the subband decomposed ECG signals and important features were determined with two different feature selection methods. These features were subjected to 5-fold cross-validation and classification was performed with RF and SVM algorithms. The results of the classification process were evaluated with AUC, Accuracy (Acc), and NPV measurement parameters (Figure 1).

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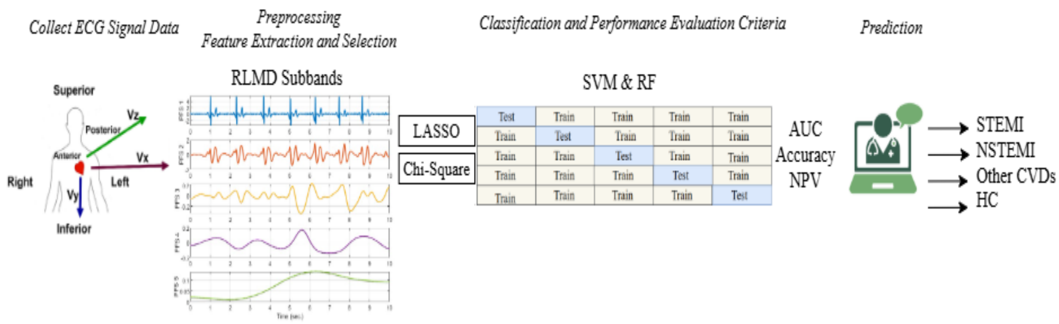

Figure 1. The process of predicting CVDs from ECG signal

Data Acquisition

In this study, ECG signals obtained from patients admitted to Erciyes University Hospital Emergency Department with chest pain complaints were analyzed. The necessary permissions to perform these analyses were obtained from Erciyes University Clinical Research Ethics Committee with approval number 2022/536. ECG signals are 12-lead and consist of 10-second recordings obtained from participants aged 18-80 years between the years 2018-2023. The recordings belonging to the healthy control groups consist of people without CVD symptoms. The remaining records consisted of participants who were blindly assessed by at least two cardiologists as STEMI, NSTEMI, and other heart conditions as a result of CVD symptoms. In this study, for each group 384 ECG recordings were analyzed.

ECG Signals Denoising and Pre-processing

In the recording of ECG signals, unwanted noises may affect the signal. These noises are caused by the network or interference of different signals. For this reason, ECG signals should be cleaned from these noises before they are analyzed. At this stage of the study, the RLMD method is applied to clean the ECG signals from noise and to analyze them and the sub-band decomposition process is explained. In the cleaning of ECG signals, the data were normalized by applying a z-score, and an IIR filter was applied from the 2-40 Hz range. ECG signals contain important information at 100 Hz and below. When we look at the power spectral densities of ECG signals, it is mostly concentrated in the range of 0-35 Hz [19]. For this reason, a filter was applied in the range of 2-40 Hz to capture important information. The filtered ECG signals were decomposed into sub-bands using the RLMD method, a technique recently proposed by Liu et al. [20]. The reason for proposing this method is to overcome problems such as elimination stopping criterion, and determination of boundaries in methods applied with similar logic such as EMD, VMD, and LMD and to improve these methods [13, 14, 17, 20]. In this study, the RLMD method was applied by using the function of the MATLAB program, and ECG signals of HC, STEMI, NSTEMI, and other heart patients were separated into five sub-bands (Figure 2).

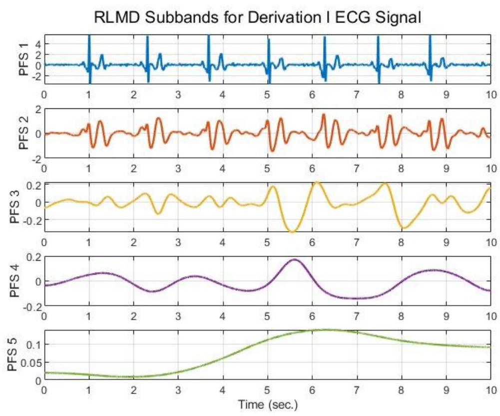

Figure 2. Sample ECG Signal RLDM Sub-bands

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Feature Extraction and Selection

The RLMD method was applied and ECG signals were decomposed into sub-bands and entropy and statistical properties were obtained from each sub-band. As entropy, Shannon, Renyi, etc. types were evaluated. Statistical features, derivatives, standard deviation, skewness, kurtosis, hjorth parameters, and maximum and minimum values of the ECG signal were calculated and included in the study [21]. These features were evaluated in a hybrid way and the ones that would both increase the computational efficiency and positively affect the performance of the classifiers were determined by applying LASSO and Chi-Square (χ^2) methods. Chi-square is a statistical method that tests the relationship between features and the target variable [22]. LASSO organizes the features depending on the coefficients of the regression variables. In this way, it can identify features that can positively affect the classification performance by reducing the prediction error [23].

Classification and Evaluation Parameters

In the classification phase of the research, RF and SVM algorithms were preferred. The features obtained after the feature selection stage in Section Feature Extraction and Selection were applied as input to these algorithms. The toolboxes of MATLAB R2023b software program were used to implement the classifiers [24]. In the training and testing phases of the classification, a 5-fold cross-validation process was performed and the average results were obtained by running five times so that the results were not randomized. The results obtained were evaluated with AUC, Acc, and NPV rates from the classification criteria. Each performance criterion rate adds different interpretations. In classification studies, performances are generally measured by the Acc rate. However, it can be misleading to look at the accuracy rate completely. The AUC rate measures the ranking scores of targets and predictions by balancing between specificity and sensitivity [25]. AUC is the rate under the Receiver Operating Characteristics (ROC) curves. The measure of this rate is determined by constructing ROC curves [26]. NPV is a special rate used in the evaluation of performance, especially in research on diagnosis [27]. Due to their importance, three performance criterion rates were obtained and the results were evaluated.

RESEARCH RESULTS

In this study, CVDs, which can be difficult and time-consuming to diagnose with the manual examination of ECG signals by clinicians, were analyzed. The analyses were performed with MATLAB R2023b software program and on a computer with an Intel i7 processor and 16 GB RAM. The 12-lead ECG signals of STEMI, NSTEMI, other cardiac conditions and healthy control participants were analyzed. RLMD method was preferred in the signal processing stage of the analysis. LASSO and Chi-square feature selection methods, which are widely used in the studies, were used to determine the features. RF and SVM algorithms were applied in the classification stage for the stability and performance comparison of the results. The classification was performed as binary, ternary, and quadruple groups. Although the results of the binary groups were better (performance criterion rates of 90% and above), the results of the analyses within heart diseases (STEMI-NSTEMI-Other CVD) and the results of distinguishing these groups from healthy groups are given in our study (Figure 3). The focus of the study was not on the differentiation of single heart disease from healthy control groups. Differentiation of CVDs, especially STEMI and NSTEMI, can be difficult and confusing for clinicians to analyze manually. It is aimed to contribute to the development of systems that can prevent this confusion and enable each group to be distinguished from healthy control groups. For this reason, we wanted to examine the groups that clinicians have difficulty distinguishing heart diseases. The classification results of the study conducted for this purpose are given in Table I-II.

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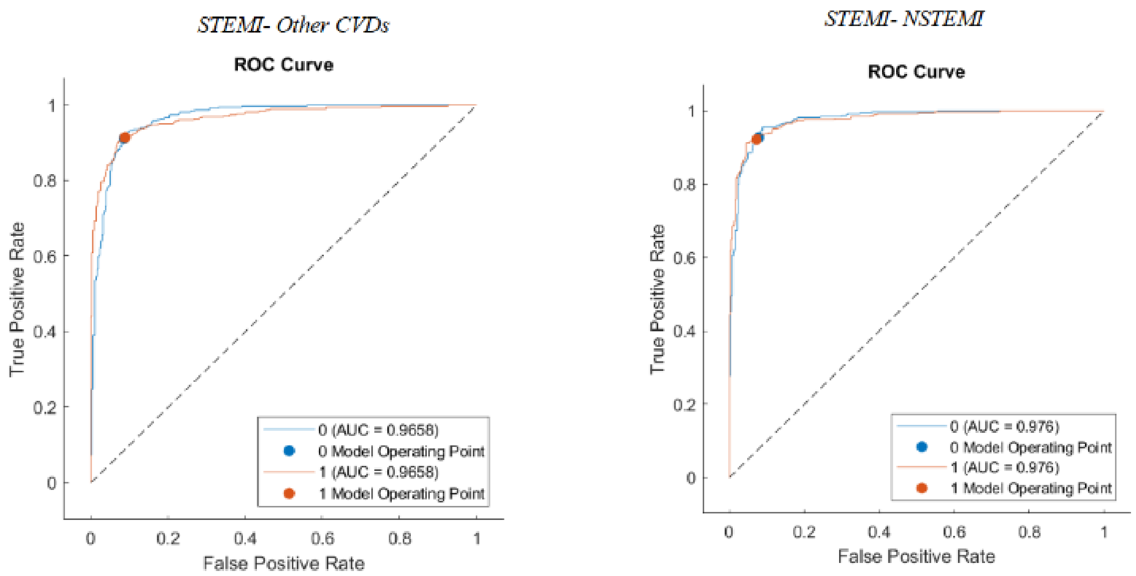

Figure 3. AUC rate and ROC graph of binary groups

Table I. STEMI-NSTEMI-Other CVDs Classification Results

	LASSO	Chi-Square
	AUC-Acc-NPV (%)	AUC-Acc-NPV (%)
SVM	85.60-70.34-85.29	85.32-69.30-84.76
RF	85.80-70.42-85.35	86.17-69.82-85.02

Table II. STEMI-NSTEMI-Other CVDs-HC Classification Results

	LASSO	Chi-Square
	AUC-Acc-NPV (%)	AUC-Acc-NPV (%)
SVM	89.62-67.38-89.13	89.13-66.60-88.86
RF	89.68-69.27-89.78	89.20-68.49-89.52

DISCUSSION AND CONCLUSION

The results given in Table I-II presented in the research results section of the study show that RF is slightly more successful when evaluated in terms of the algorithm used. In terms of feature selection methods, it is seen that the LASSO method is slightly more successful. The results of the two classifiers and feature selection methods applied in this study are close to each other. This is important for the stability and consistency of the results of the proposed study. In this study, the classification results were evaluated especially with accuracy, AUC, and NPV rates. The accuracy rate is analyzed in almost all similar studies. However, this may be misleading. In addition to this rate, NPV and AUC rates should be evaluated. Because a high NPV rate means that the evaluation of a negative result of a particular test is most likely to be correct. A high NPV rate also indicates that negative test results are reliable [27]. A low ratio does not give confidence for a complete diagnosis and additional tests may be needed. AUC rate and ROC curve can provide important information, especially in the evaluation of medical data [25]. The ROC curve is drawn according to the true positive rate (TPR) and false positive rate (FPR). A high TPR rate and a low FPR rate are desired for classifier models [28]. In the study, especially the average AUC, NPV criterion rates showed success above 84%

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in both classifiers and the groups examined. The AUC rates and ROC curve graphs obtained with the LASSO method and SVM, and RF algorithms are given in Figure 4.

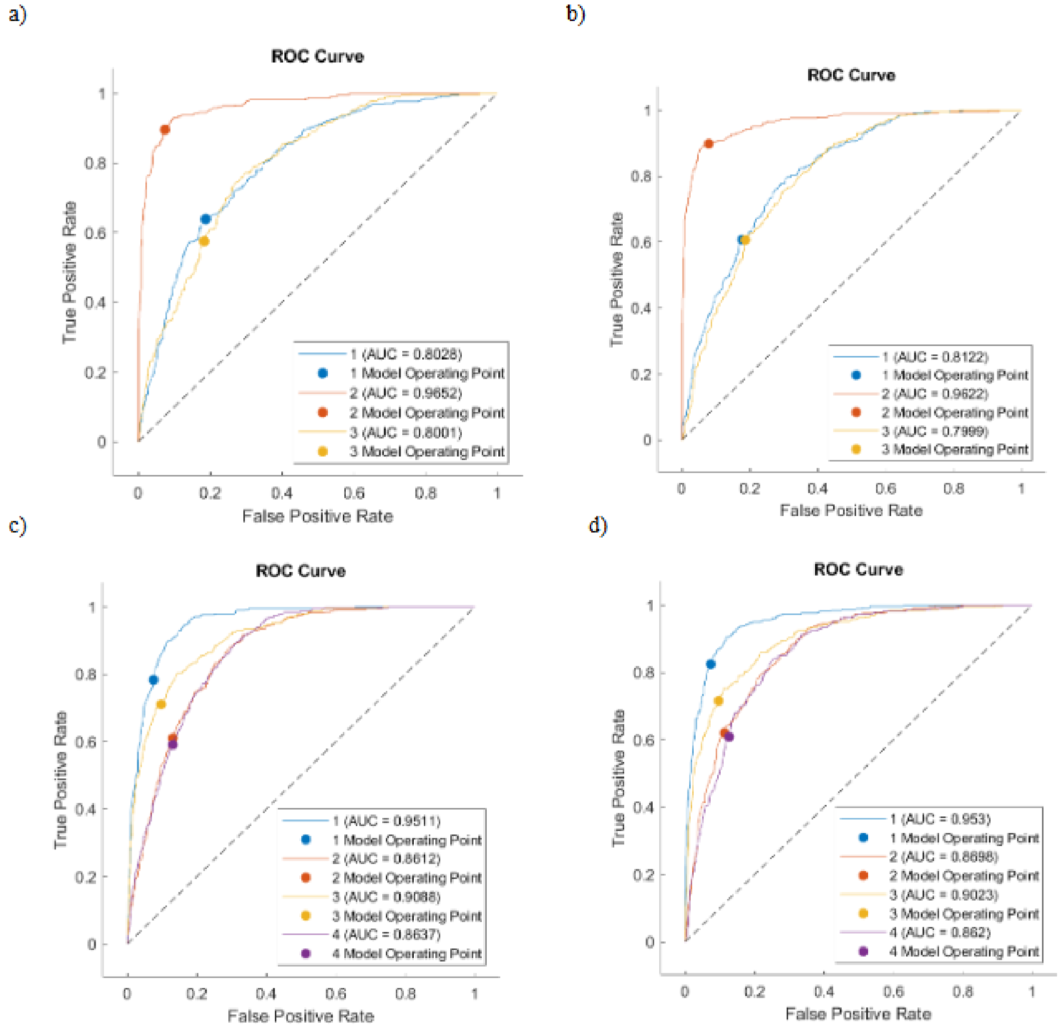

Figure 4. a) SVM (1NSTEMI-2STEMI-3Other CVDs), b) RF (1NSTEMI-2STEMI-3Other CVDs), c) SVM (1HC-2NSTEMI-3STEMI-4Other CVDs), d) RF (1HC-2NSTEMI-3STEMI-4Other CVDs)

Figure 4 (a, b) shows that the model applied in the proposed study can discriminate the STEMI group (2) most successfully (over 96%). When the results given in Figure 4 (c, d) are analyzed, it is seen that HC groups (1) are distinguished more successfully and at a higher rate than heart diseases (over 95%). Figure 4 (c, d) graphs, the STEMI group (3) is also differentiated more successfully than the others (over 90%). In the proposed study, it is important that both HC groups and STEMI can be differentiated from heart diseases at a high rate.

When the studies on the analysis of heart diseases from ECG signals with machine learning algorithms are examined, VMD, EMD, and similar signal decomposition techniques are generally used in the feature extraction phase. In this way, ECG signals are more easily analyzed and important information is preserved [29-31]. The RLMD method is superior to methods such as VMD, EMD, and LMD for signal processing and is more suitable for time-frequency analysis and feature extraction of signals [14]. In support of this information in the literature, the results obtained with the RLDM method in this research are quite successful. The RLDM method has been recently introduced to the literature and although it has been applied in different fields, it has been applied very little in the analysis of ECG signals [18]. For this reason, we could not compare our research results one-to-one because of both the low use of RLMD and the fact that many studies in the literature mostly analyze binary groups as HC-heart disease with methods

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such as EMD and VMD. As can be seen in the results in Table I-II, the low accuracy rate in this study can be criticized and can be seen as a deficiency. However, many studies have focused on distinguishing a single heart disease from healthy controls and there are deficiencies in the analysis of heart diseases [32, 33]. If we wanted to analyze only binary groups, high accuracy rates could have been achieved. This situation has been analyzed in another study we contributed to the literature [29]. As can be seen in the results in Figure 3, in this study, AUC rates of 90% and above were achieved in the analysis of binary groups. In this study, we wanted to analyze the most common heart diseases within themselves and by including HC groups to be different from many other studies and to focus on a problem specified by clinicians. For this reason, only the results of the classification of the specified groups are focused on. In future studies, the accuracy rate can be improved by increasing the number of data, and by increasing the number of data, deep learning methods applied in recent studies [32, 34] can be tried. It is also important that 12-lead ECG signals are analyzed in this study to obtain more information than single-lead signals [6]. The presented research will be one of the very few researches that analyze ECG signals by applying the RLMD method. In this way, we think that the presented research is different from the studies in the literature and can find a solution to an important problem.

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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