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Analysis of Coronary Heart Diseases by Kinetic Features: Applying Variational Mode Decomposition to ECG Signals and Classification Using Machine Learning Algorithms

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Abstract **–** This study presents an approach for the diagnosis of myocardial infarction (MI) and other coronary heart diseases using 12-lead electrocardiogram (ECG) signals. In the presented approach, 12-lead ECG signals recordings of MI types (STEMI-NSTEMI), other heart diseases (OHD) and healthy control (HC) participants, who presented to the Emergency Department of Erciyes University Hospital for heart disease, were used. In the first stage, the noise-cleaned ECG signals were decomposed into subbands by applying the Variational Mode Decomposition (VMD) method and kinetic features were obtained, and the ones that would positively affect the performance of the classifiers were determined by Chi-square test. In the classification stage, these features were evaluated by Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) algorithms, and AUC, Accuracy, and Negative Predictive Value ratios were obtained. Classification procedures were performed for HC-OHD, HC-MI (NSTEMI+STEMI), and STEMI-NSTEMI-OHD groups. When evaluated in terms of AUC, rates that can be considered successful (80% and above) were obtained. The findings of this research may contribute to the systems that can be developed for the rapid and accurate diagnosis of coronary heart diseases from ECG signals, which can be difficult to interpret manually.

Keywords *– Coronary heart disease, 12-lead electrocardiogram (ECG) signal, Kinetic features, Variational mode decomposition, Machine learning algorithms.*

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I. INTRODUCTION

Coronary heart disease is the leading cause of death in the world [1]. The diagnostic device used for the diagnosis of such heart diseases is the electrocardiogram (ECG), which is a non-invasive measurement [2, 3]. Fast and accurate diagnosis of Myocardial Infarction (MI), a type of coronary heart disease, is important for the patient's life. MI is divided into ST-elevation MI (STEMI) or non-ST-elevation MI (NSTEMI), which occur in the waves in the ECG signal. These heart diseases can be difficult and complex to analyze with standard 12-lead ECG signals [4]. For this reason, thanks to the analyses made with devices that provide computer-aided automatic diagnosis of 12-lead ECG signals developed with recent research, patient-specific diagnosis of heart diseases is faster and can help cardiologists [3-5]. Artificial intelligence techniques have an important role in the development of these devices.

Most of the studies for predicting heart diseases are focused on obtaining distinctive diagnostic features from ECG signals and classifying them with machine learning algorithms [6]. In these studies, signal processing methods such as Fourier transform and wavelet analysis are usually applied to extract time-dependent or morphological features from ECG signals [6-8]. These features are applied as input to machine learning algorithms such as SVM [9], k-Nearest Neighbors (k-NN) [10], ANN [11], and many other classifiers to predict diseases [12]. Using these machine learning methods, studies are reporting high accuracy rates in the development of decision support systems that can assist healthcare professionals in the diagnosis of MI. These studies generally consist of signal preprocessing, feature extraction, or selection from signals and classification [11]. Sahu et al. proposed a new technique for MI detection and localization [12]. In their proposed technique, ECG signals are decomposed into components using the variational mode decomposition (VMD) method, and the significant features from these components are selected by the regularized neigh bourhood component analysis method and evaluated in the k-NN classifier. In their study on MI detection, Anwar et al. applied the discrete wavelet transform (DWT) method in the preprocessing step and deep auto encoder method in the feature extraction step to ECG signals and classified them with k-NN algorithm [13]. In another study on MI detection, three different techniques, namely DWT, Empirical Mode Decomposition (EMD), and Discrete Cosine Transform (DCT), were applied to ECG signals, and the obtained features were analysed with k-NN classifier [14]. Similarly, in the study by Zeng et al. on MI prediction [15], a model based on tunable quality wavelet transform (TQWT) and VMD methods was proposed for feature extraction from ECG signals, and classification was performed with neural network-based algorithms. Similar to the previously described research, features are retrieved using methods as Random Forest (RF), Naive Bayes, SVM, Decision Tree, EMD, VMD, wavelet transform, etc. [15, 16]. There are many studies on the classification of the prediction of MI with machine learning algorithms [17-19]. The results obtained in these studies are analyzed in detail in the discussion section.

In this study, 12-lead ECG signals obtained from our recordings of HC, STEMI, NSTEMI, and (OHD) other heart disease (non-NSTEMI and STEMI) groups were analyzed. In the analysis, ECG signals were decomposed into VMD sub-bands, and various kinetic features representing the dynamic and statistical properties of cardiac activity were obtained from each sub-band. From these features, the ones that will positively affect the classifier performance were determined by the Chi-square test (χ^2), and the classification process was performed using machine learning algorithms ANN, SVM, and RF. With the classification process, HC-OHD, STEMI-NSTEMI-OHD, and HC-MI (NSTEMI+STEMI) groups were predicted. The flow diagram summarising the study is given in Fig.1 and detailed explanations of the procedures are given in Section 2. In Section 3 of the study, the findings obtained and the comparison of these findings with the results obtained in similar studies are discussed. In the last section, the results of the study are summarised and future studies are mentioned.

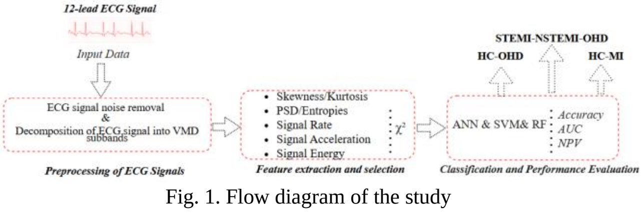

Fig. 1. Flow diagram of the study

II. Method

A. Data acquisition

The ECG signals analyzed in this study were taken from people who came to Erciyes University Hospital Emergency Department with chest pain between 2018-2023 (Ethics decision no: 2022/536). The recordings consist of 10-second 12-lead ECG signals with a sampling frequency of 500 Hz. The healthy group consisted of participants aged between 18 and 80 years without myocardial infarction or other heart disease. The NSTEMI, STEMI, and OHD groups consisted of participants aged 18-80 years with clinical findings diagnosed by at least two cardiologists. In the study, 159 records were analyzed for each group.

B. Preprocessing of ECG Signals

At this stage of the study, some methods were applied for pre-processing and decomposition of ECG signals. This stage is necessary for better analysis of ECG signals and accuracy of the signal. In the first stage, after the ECG signals are collected, filtering is applied to remove low/high frequency noise and fundamental errors. A low-pass filter with a cut-off frequency of 45 Hz was applied to remove high-frequency noise, and a high-pass filter with a cut-off frequency of 0.5 Hz was applied to correct baseline fluctuations (Fig.2). After filtering, each ECG lead was decomposed into sub-bands using the VMD method (Fig.3). The VMD method proposed by Dragomiretskiy and Zosso decomposes the original input signal into intrinsic mode components of different frequency and amplitudes [20, 21]. Thanks to this method, the input signal can be analyzed more easily and important information in the time and frequency domain is stored [15]. In this study, various kinetic and statistical features representing the dynamic and statistical properties of cardiac activity were extracted from each sub-band of ECG signals decomposed into intrinsic mode components by the VMD method.

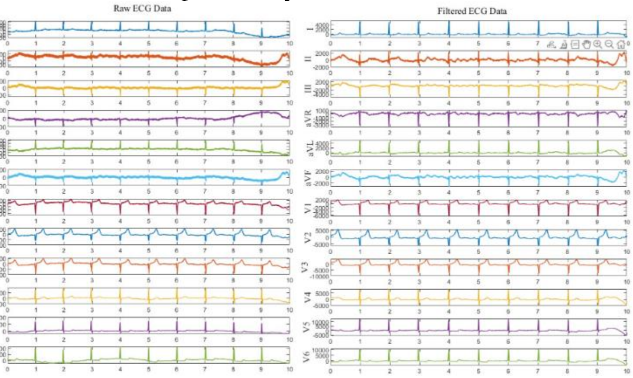

Fig.2. Original and filtered 12-lead ECG signals

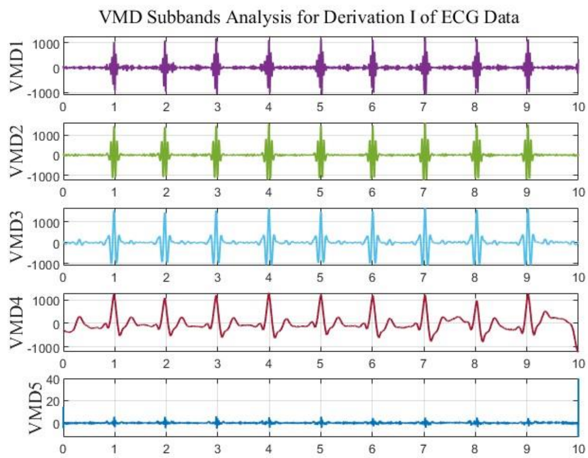

Fig. 3. Sample ECG signal decomposed into subbands by VMD method

C. Feature extraction and selection

Various kinetic and statistical features representing the dynamic properties of cardiac activity were extracted from each sub-band of ECG signals decomposed into sub-bands by applying the VMD method. Kinetic features are parameters such as the average rate of change of the signal, instantaneous velocity/acceleration, maximum and minimum values for instantaneous velocity/acceleration indicating the highest change points of the signal, average velocity, and average acceleration indicating the overall activity of the signal, and energy of velocity/acceleration signals. These features were used to determine the rate of change, acceleration, and energy density of the signal over time. The statistical features obtained in the study include standard deviation, which measures the amount of variation or spread in the ECG signal, skewness, which shows the asymmetry of the amplitude distribution of the signal, and kurtosis, which measures the degree of tailedness of the amplitude distribution of the signal. In the frequency domain, the power spectral density of each subband in the range of 0.5-45 Hz was calculated. In addition, peak-to-peak amplitude and entropy-based features of each subband were calculated to provide information about the amplitude distribution and complexity of the signal. It has been reported that such features are effective in the analysis of ECG signals [22]. In the feature selection process, the Chi-square test was applied to reduce the size of the dataset and to determine the features that will positively affect the performance of the classifiers [23], and prediction was performed between groups in the classification processes.

III. Experimental Results and Discussion

In this study, 12-lead ECG signals obtained from patients with different coronary heart diseases and healthy groups in the emergency department were analyzed by applying the VMD method and three different machine-learning algorithms. As a result of the analysis, HC-OHD, MI (NSTEMI+STEMI)-OHD, and HC-MI groups were classified and heart diseases were predicted. All operations in the study were performed using MATLAB R2023b program on a computer with Windows 10 operating system, Intel i7 processor, and 16 GB RAM. In the classification process, 5-fold cross-validation was applied and Area Under Curve (AUC), Accuracy (ACC), and Negative Predictive Value (NPV) parameters were obtained. Accuracy is the parameter that measures the accuracy of the classification process [24, 25]. AUC is a parameter that measures the balance between specificity and sensitivity and is a measure of the accuracy of classification [25]. NPV is used in diagnostic test performances and is the probability of the disease occurring [24]. The classification results obtained by applying SVM, ANN, and RF algorithms are given in Table 1.

Table 1. Classification Results

Classifier (%)	HC-MI	HC-OHD	MI-OHD
	AUC-ACC.-NPV	AUC-ACC. NPV	AUC-ACC.-NPV
SVM	81.70-74.76-74.54	80.37-77.11-76.10	70.55-66.45-67.10
ANN	80.81-73.52-75.50	80.92-74.60-73.15	68.79-65.50-66.44
RF	82.22-71.34-70.59	85.46-76.80-74.72	73.73-68.10-67.26

According to the results in Table 1, it is seen that the classification of coronary heart diseases with HC groups is more successful than the classification of heart diseases among themselves. All three machine learning algorithms were close to each other and successful results were obtained in terms of AUC ratio. When the AUC ratios are analysed, the RF algorithm showed the most successful performance. It is normal that the classification results of STEMI-NSTEMI and other heart diseases, which have differences that can be difficult to see in the ECG signal, show slightly lower performance. The algorithm could not fully reveal the differences between these signals. With the techniques and models to be developed in the future, more successful results can be obtained in the classifications of these diseases. In the studies conducted in the literature, mostly MI and HC groups were analyzed and classified with artificial intelligence techniques [16-19, 25, 26]. It is seen that there are fewer studies on the analysis of MI types and other heart diseases [27]. When we look at the multiple classification studies analysing the types of cardiovascular diseases as in this study [28-30], it is seen that the data are unevenly distributed. In the classification results obtained with this situation, an accuracy rate of 90% and above was obtained. The common point of these studies is that they applied deep learning models in the classification phase [27, 28, 30]. However, we do not think that the samples in our study are sufficient for deep learning. In order to train deep learning models, the sample size should be sufficient [31]. For this reason, in this study, the analysis of heart diseases was analysed with machine learning methods. In future studies, the number of samples can be increased and analyzed with deep learning models and we can improve our results. In our results in this study, it is important that our AUC ratios, which provide medically important information [25], are 80% and above in the classification of HC and heart diseases. In the classification of heart diseases among themselves, not-bad AUC ratios were also achieved. We acknowledge that our results show lower performance compared to the results of similar studies [14-16]. However, we also think that our study has contributions and advantages to the literature. The contributions and advantages of this study can be explained as follows:

- It is important that the ECG signals used in the study are not from a ready-made dataset but from our own recordings and that these signals are 12-lead and provide more information for clinical evaluations than single-lead signals [32].
- While most of the studies in the literature focus only on the classification of MI-HC groups [27-30], in this study, in addition to the MI-HC group, heart diseases were classified and analysed among themselves and with HC groups.
- Machine learning algorithms SVM, ANN and RF were used for classification and the performance of different models were compared and the algorithm with the best performance was determined.
- Another point that we consider important is the application of the VMD method, which captures the signal information at a significant rate, in such a study with original data. Because the VMD method provides easier analysis of the ECG signal and can reveal the modes containing the dominant energy in the cardiac vector signal in ECG [15].

This research can be considered as a preliminary study. For this reason, we think that it has some shortcomings. The deficiencies and disadvantages of the research can be explained as follows:

- Examining only the VMD method in the study can be seen as a deficiency. In future studies, in

addition to the VMD method, different techniques and features with similar characteristics can be tested and their performances can be compared.
- In addition to the data consisting of our records, the results of the study can be strengthened by testing the method applied with a similar data set.

IV. CONCLUSION

This research has presented an effective approach to diagnose MI and other cardiac disorders from coronary heart diseases using 12-lead ECG signals. Diagnosis of coronary heart disease by manually analyzing ECG signals can be complex and difficult. For this reason, there is a need to develop systems that can provide effective and fast diagnosis. In this study, which is not only analyzed as HC-heart diseases but also analyzed within heart diseases, we think that the findings obtained can contribute to the systems that can be developed. With future research, the deficiencies of the study can be improved and models can be developed by obtaining more successful performance parameters.

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Authors' Contributions

Methodology and analysis, F.L.; validation, F.L., F.O.B, A.G, and S.İ.; writing, original draft preparation, F.O.B; review and editing, F.L, F.O.B, A.G, S.İ. and A.Z.; data collection, A.Z.

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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