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Diagnosis of Acute Coronary Syndrome with CNN and LSTM Based Deep Learning Model

Abstract: - Early and accurate diagnosis of acute coronary syndrome (ACS) and its subtypes is essential for patient health. The aim of this study is to develop a deep learning approach utilizing electrocardiography (ECG) signals to classify ACS and its different types. The model was constructed using a combination of convolutional neural network and long short-term memory structures to categorize ECG signals representing acute myocardial infarction with ST-elevation (STEMI), myocardial infarction without ST-elevation (NSTEMI), and healthy individuals. The dataset comprises 12-lead ECG signals collected from patients who presented with chest pain at the Erciyes University Hospital Emergency Department. ECG data were processed to remove noise using notch, low-pass, and high-pass filters, and then standardized using z-score normalization. Model performance was assessed through k-fold cross-validation, calculating metrics such as accuracy, sensitivity, specificity, precision, F1 score, and classification rate. With 5-fold cross-validation, classification accuracy was observed to be 0.928 ± 0.0172 for the ACS-Normal group, 0.891 ± 0.0083 for the NSTEMI-Normal group, and 0.886 ± 0.02275 for the STEMI-Normal group. These findings suggest that the proposed deep learning model is effective in distinguishing ACS and its subtypes, showing promise for future integration into clinical applications.

Keywords: Acute Coronary Syndrome, Deep Learning, ECG, CNN, LSTM, Classification.

I. INTRODUCTION

All diseases that adversely affect the circulatory system are defined as cardiovascular diseases. Among these diseases, acute coronary syndrome (ACS) is a leading cause of mortality globally and in our country. The type of acute coronary syndrome with the highest risk of death is acute myocardial infarction. Myocardial infarction (MI) occurs due to a blockage in the coronary arteries that interrupts the blood flow, depriving the heart of oxygen and nutrients, which may lead to tissue damage or necrosis (death of tissue). As this blockage prevents the flow of blood carrying oxygen and nutrients to the heart, tissue damage or necrosis can occur in parts of the heart. In order to use the definition of MI, there is evidence of myocardial necrosis consistent with myocardial ischaemia, and in order to reach this evidence, there are diagnostic criteria for MI that must be observed. There are some biomarkers measured and imaging modalities used to reach the diagnosis of MI. The first biomarker measured in patients presenting with chest pain, one of the most common symptoms of MI, is cardiac troponin (kTn) and the primary imaging procedure is Electrocardiography (ECG). Significant ST segment-T wave (ST-T) changes or left bundle branch block (LBBB) and abnormal Q waves on ECG, along with fluctuating troponin levels, meet the diagnostic criteria for MIpoo [1]. When we look at the ECG classification of MI, it is divided into two types 'ST-elevation MI' (ST-elevation myocardial infarction-STEMI) in which ST elevation is seen in two related leads and 'non-ST-elevation myocardial infarction-NSTEMI' in which ST elevation is not seen. In addition, most patients with MI develop ECG-Q waves, whereas some may not develop Q waves [1].

Chest pain is one of the most common symptoms of acute myocardial infarction. However, an important problem arises in patients presenting with this complaint because it has been observed that 60% to 90% of these patients do not have acute myocardial infarction. Emergency physicians find it difficult to correctly differentiate NSTEMI from non-cardiac causes (e.g. gastrointestinal reflux, pulmonary embolism, cholecystitis, and pleural and pericardial irritations) [2]. NSTEMI is more common than STEMI, but NSTEMI is more difficult to diagnose and therefore its prevalence is not easy to quantify [1]. Nowadays, while the prevalence of STEMI is decreasing, the increase in NSTEMI is remarkable. Hospital mortality is higher in the STEMI group, but for STEMI, these deaths occur in the early period, whereas in NSTEMI, progression to mortality occurs within days and weeks, and ultimately, at the end of the 6 months, NSTEMI and STEMI mortality rates converge [3]. The most important

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reason for this similarity is that patients presenting with NSTEMI are generally older and have comorbidities such as diabetes and kidney disease [2]. Current diagnostic criteria for STEMI miss up to 30% of ACS patients in need of early diagnosis and treatment, a significant proportion [4]. As can be seen, the current diagnostic criteria are insufficient for the NSTEMI class.

With this proposed study, we aim to provide a classification that will increase the diagnostic accuracy of myocardial infarction by using today's artificial intelligence technologies. One of the popular neural network architectures in deep learning, which is a sub-branch of artificial intelligence, is Convolutional Neural Networks (CNN), and the other architecture is Long Short-Term Memory (LSTM). The functioning and architecture of CNNs are described in detail by LeCun et al. (1998). CNNs receive input data in height, width, and depth dimensions and extract features from these data through convolution layers. Convolution layers shift the input data using filters and create feature maps. Non-linear activation functions such as ReLU are used to allow the model to learn non-linear relationships. Pooling layers minimize the size of feature maps, reducing computational cost and increasing generalization capability.

Finally, fully connected layers and the output layer perform classification operations using the obtained features. CNNs show high performance especially in image recognition and processing areas thanks to their features such as local connections and weight sharing [5]. Long Short-Term Memory Networks, often called 'LSTM', are a special type of Recurrent Neural Network (RNN) that can learn long-term dependencies. They were introduced by Hochreiter and Schmidhuber (1997) and have been developed and popularised by many others in subsequent studies. The main components of LSTM are cell state and gate mechanisms. The cell state allows the network to store long-term information and three types of gates control this state: input gate, forget gate, and output gate. The input gate decides whether new information is added to the cell, while the forget gate determines how much of the existing information in the cell is retained. The output gate controls which information from the cell state is transferred to the output. These mechanisms enable LSTM to overcome the long-term dependency problems of classical RNNs by increasing its ability to learn and maintain dependencies over time [6].

Using a structure that integrates CNN and LSTM architectures enables us to learn spatial and temporal features of the data together by utilizing the unique aspects of both architectures. The data will first be fed to the CNN layers and high-level feature vectors will be obtained. The resulting features are fed to LSTM as time series data, and time dependencies are learned and the final prediction is made [7]. This integration increases the prediction accuracy. Table 1 below briefly summarises the LSTM-CNN studies for ECG in the literature in the last 6 years.

Table I. Literature studies in the last 6 years using LSTM-CNN for ECG signals.

Reference	Participants	Data Information	Features	Classifier	Accuracy (%)
Rai et al.[8]	MI-Normal Total:123998beats	MITDB and PTBDB	ECG Segments lead-II	CNN-LSTM	99.88
Xu et al. [9]	48 records	MITDB	ECG Rhythms	CNN+Bi-LSTM	95.90
Abdullah et al.[7]	549 records	PTBDB	ECG Segments	CNN+LSTM	98.13
Kavak et al.[10]	STEMI: 270 OTHER:270	Dataset from Hualien Tzu Chi Hospital	ECG Images	2D CNN	96.3
Xiao et al.[11]	ST:266275 Non-ST:300000	LTST	ECG Images	CNN	89,6
Reasat et al.[12]	MI: 3222 NORMAL: 3055	PTB	ECG Segments	CNN	84,54
Tadesse et al.[13]	MI: 148 NORMAL: 52	PTB	ECG Segments (12 Leads)	CNN-LSTM	94
Gumpfer et al.[14]	114 Records	Kerckhoff Biomarker Registry	ECG and MRI Images	CNN	78

Reference	Participants	Data Information	Features	Classifier	Accuracy (%)
Makimoto et al.[15]	MI: 148 Non-MI: 141	PTB	ECG Segments	6-Layer CNN	81
Rashid et al.[16]	MI: 44214 NORMAL: 6157	PTB	ECG Segments	BCNN	90,29
Liu et al. [17]	MI:148 NORMAL: 52 (368 Records)	PTB	ECG Segments	CNN-Bi-LSTM	99.90
Lui et al.[18]	MI: 368 NORMAL: 80	PTB and AF Challenge	ECG Segments (lead-I)	CNN-LSTM	97.2
Feng et al.[19]	MI: 148 NORMAL: 52	PTB	ECG Segments (lead-I)	16-Layer CNN-LSTM	95.4
Lih et al.[20]	NORMAL: 92 MI: 148	PTB	ECG Segments (lead-II)	16-Layer CNN-LSTM	98.51
Goto et al.[21]	ACS: 249 NORMAL: 300	PTB	ECG Signals 12 Leads	1D CNN-LSTM	83
Jothiramalingam et al.[22]	MI:632940 NORMAL: 127188	PTB, MIT-BIH, European ST Dataset	ECG Segments 12 Leads	2D CNN- Bi-GRU	99,83
Dey et al.[23]	MI: 367 Non-MI: 70 NORMAL: 80	PTB	ECG Signals 12 Leads	1D CNN-Bi-LSTM	99,246
Martin et al.[24]	MI: 50732 NORMAL: 10123	PTB	ECG Segments (lead-II)	LSTM	89,56

II. Material And Methods

In this study, it was aimed to classify ACS-normal, STEMI-normal, and NSTEMI-normal using 12-lead ECG signals. The process steps performed for this purpose are given in Fig. 1.

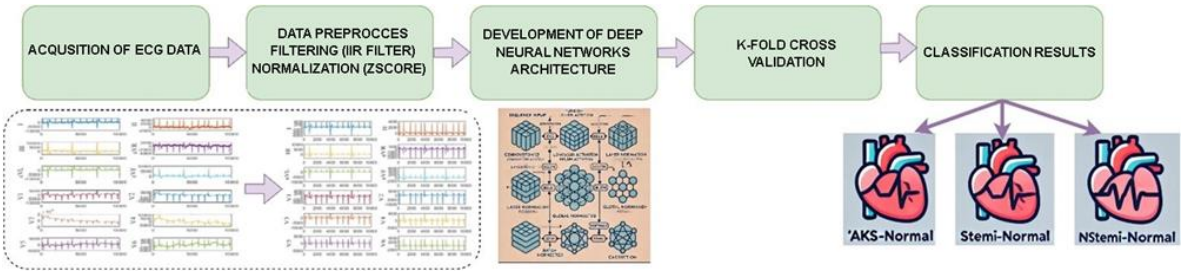


Fig. 1 Flow chart of this study

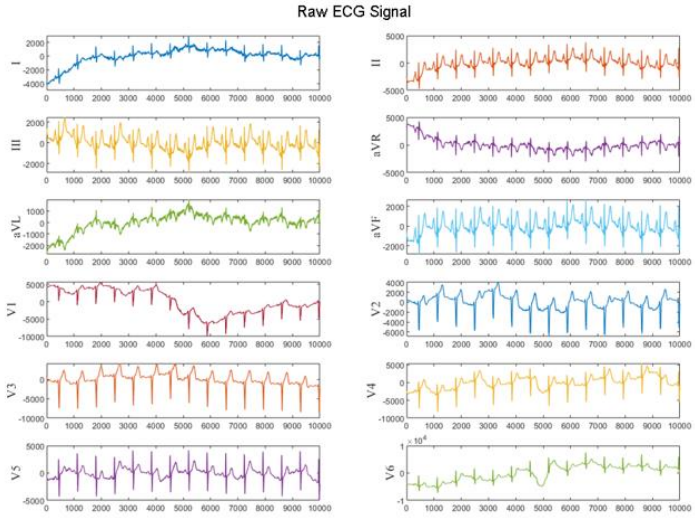
A. Acquisiton of ECG Data

It is aimed to classify ACS-normal, STEMI-normal, and NSTEMI-normal using 12-lead ECG signals in this study. As part of this research, 12-lead ECG signals collected from patients presenting with chest pain to the Erciyes University Hospital Emergency Department were analyzed. Ethical clearance for the utilization of hospital records was granted by the Erciyes University Ethics Committee. ECG data from 1000 healthy individuals, 500 STEMI patients, and 500 NSTEMI patients were used for The aim of this study is to develop a deep learning approach each group. The dataset comprises 10-second, 12-lead ECG recordings retrieved retrospectively from the archives of Erciyes University Faculty of Medicine Hospital between 2018 and 2023. In the healthy group, ECG records of individuals aged 18-80 years who did not have a myocardial infarction, heart disease, or coronary artery disease were analyzed. In the patient group, ECG records of patients aged 18-80 years with STEMI and NSTEMI or suspected ACS with chest pain were analyzed. Disease classification, ST elevation or depression on ECG, additional clinical observations, and angiography outcomes were assessed independently

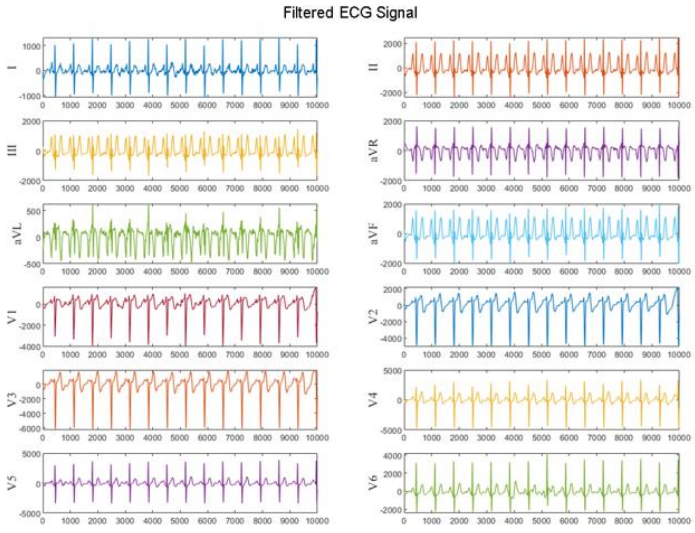
by at least two cardiologists. Patients with narrowing on angiography and ST elevation on ECG were classified as STEMI, while those with ECG changes other than ST elevation, narrowing on angiography, and elevated troponin levels were classified as NSTEMI.

B. Preprocessing of ECG Signals

In this stage of the study, various filtering techniques were used for preprocessing and separation of ECG signals. In the preprocessing stage, the sampling frequencies of the data sets used were set to 500 Hz. For noise removal, first of all, a notch filter was used to eliminate power line noise at a certain frequency. The notch filter filtered the frequencies in bandwidth between half-power points, eliminating electrical noise at certain frequencies, especially 50/60 Hz. Then, a 3rd order IIR low-pass filter was designed to clean high-frequency noise. This filter had a cut-off frequency of 40 Hz and eliminated low- and high-frequency noise while preserving high- and low-frequency components. At the same time, a 3rd order IIR high-pass filter with a cut-off frequency of 2 Hz was used to suppress low-frequency components and eliminate background noise. In addition, the signals with eliminated noise were normalized with z-score. The figure below shows the ECG signals before and after noise elimination.



a)



b)

Fig. 2. Example of ECG signal a) before b) after filter applications used for noise elimination

C. Development of Deep Neural Networks Architecture

A one-dimensional (1D) deep neural network architecture consisting of CNN and LSTM layers was developed for the classification of ECG signals. During the development of the architecture, models consisting of different layers were tested and the architecture with the best results was presented. In the obtained model, the Input Layer,

1D Convolution Layer, ReLU Layer, Layer Normalisation Layer, LSTM Layer, Fully Connected Layer, Softmax Layer, and Classification layers were used.

In the model used; the Input Layer is the first layer that determines the size of the data and accepts the input data. No operation is performed on the data in this layer. 1D Convolution Layer applies the convolution process in sequential data such as time series. The ReLU Layer is used as an activation function and equates negative values to zero to make the output of the layer valid. The Normalisation Layer stabilizes the distribution of weight values by normalizing each data sample. The LSTM Layer is a type of feedback neural network layer that is particularly effective on sequential data sets such as time series and natural language processing. It manages long-term dependencies through memory cells. The global average pooling layer performs global average pooling on 1D data. It is usually used after the CNN structure. It reduces the size of the feature maps and generates the output of the network. The stack normalization layer normalizes the output of the previous layer. This normalization can help to train the network faster and more consistently. It can also improve the generalization performance of the model by reducing the risk of overfitting. The Fully Connected Layer flattens the input data and then processes each output in a connected manner. The Softmax Layer converts the output into a probability distribution in multiple classification problems. Classification Layer is a classification layer that will assign the outputs of the model to real classes. The model developed in this study is shown in Fig. 3.

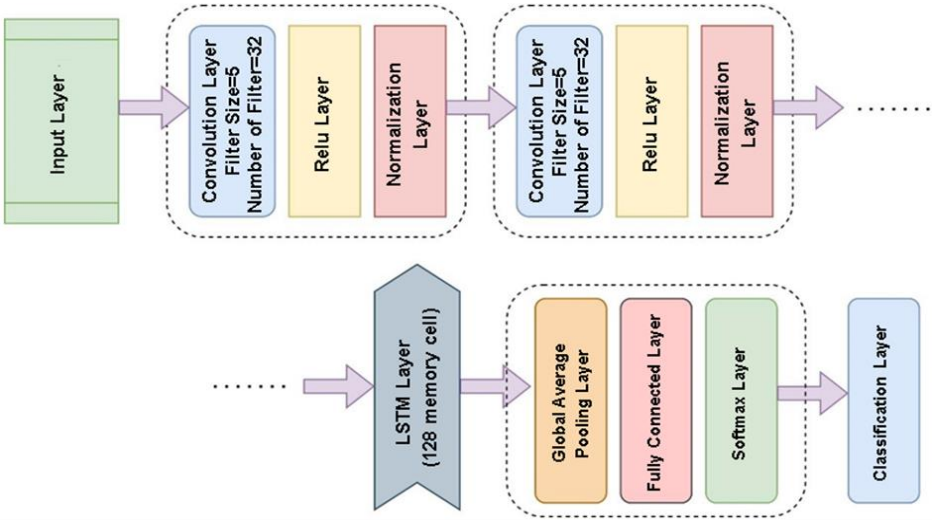


Fig. 1 Developed Deep Neural Network Architecture

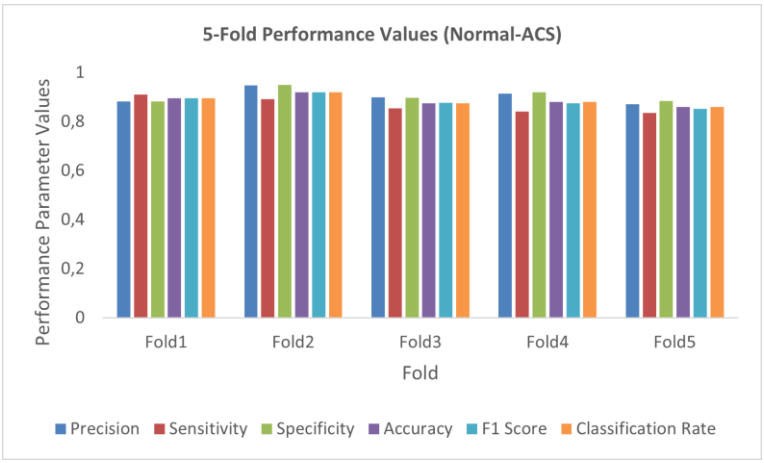
Adam optimization algorithm is used for training the developed model. This algorithm is a gradient-based optimization algorithm and is widely used in deep learning models. In the Adam algorithm, an adaptive learning rate is set based on the previous derivatives and each parameter has its learning rate. The number of iterations determines how many times the model is trained on the training dataset and in this study, the number of iterations is set to 10. The number of samples to be used in each training iteration is expressed as mini size. When training on a large data set, it may be more efficient to use the entire data set in mini chunks instead of using it all at once. In this study, the mini-batch size is set as 64. The parameters (weights) of the model updated at each step are controlled by the learning rate. A lower learning rate allows the model to learn more steadily and slowly, but convergence may take longer. In this study, the learning rate is set as 0.001.

III. Research Results And Performance Evaluation Of Classifier Model

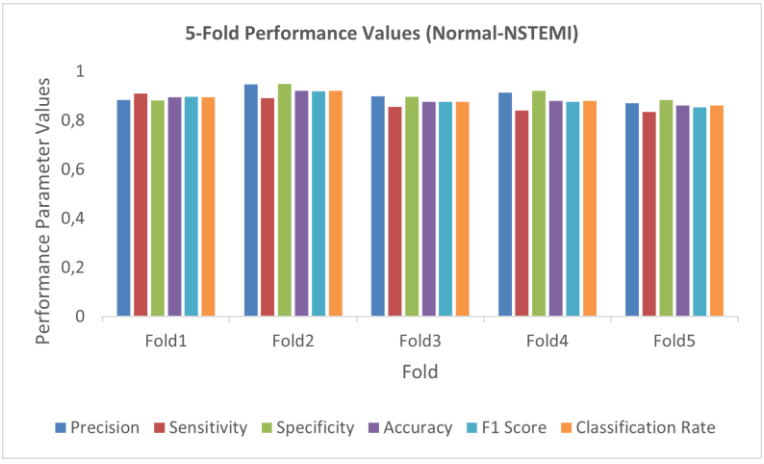
In this study, k-fold cross-validation (CV) method was employed during the classification stage. With k-fold CV, the data is partitioned into k equal segments. For each iteration, k-1 segments are used for model training, while the remaining segment is reserved for testing the model. This procedure repeats k times, and the average of the outcomes is taken to assess the model's performance. Here, a 5-fold CV approach was chosen, meaning that in each iteration, 20 percent of the data was allocated for testing, while 80 percent was used for training. Following each cross-validation cycle, performance metrics such as accuracy (Acc), sensitivity (Sens), specificity (Spec), precision (Prec), F1-score (F1), and classification rate (CR) were computed. The averages of these metrics were used to assess the performance of the classifier models. The average performance values calculated with 5-fold validation for all three binary classification groups are presented in Table 2. In addition, as shown in Fig. 4, 5-fold CV results for each binary classification group are given separately. The graphs show the accuracy, sensitivity, specificity, precision, F1 score, and classification rate metrics for each fold.

Table II. Classification performance metrics and values

Groups	Accuracy	Sensitivity	Specificity	Precision	F1-Score	Classification Rate
ACS-Normal	0.949 ±0.0050	0.906 ±0.0304	0.951 ±0.0068	0.928 ±0.0172	0.927 ±0.0168	0.928 ±0.0172
NSTEM - Normal	0.897 ±0.0338	0.885 ±0.03026	0.901 ±0.0259	0.891 ±0.0083	0.890 ±0.0057	0.891 ±0.0083
STEMI-Normal	0.9023 ±0.0002	0.8659 ±0.0326	0.9062 ±0.0286	0.886 ±0.0227	0.8834 ±0.0247	0.886 ±0.02275



a)



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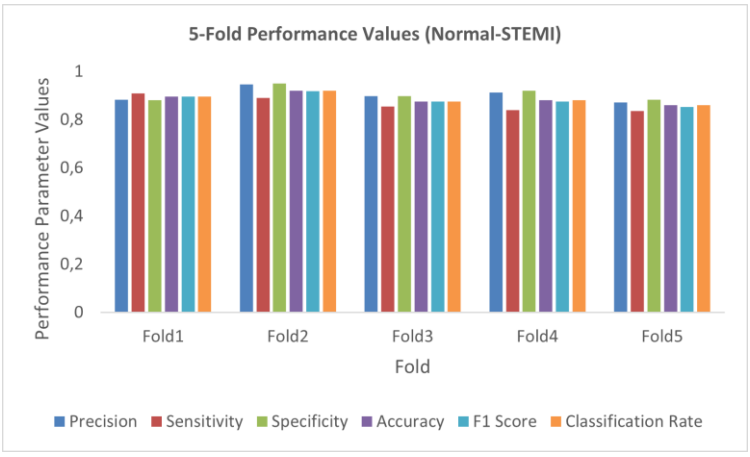

c)

Fig. 4 5-fold classification performance parameter values of a) Normal-ACS, b) Normal-NSTEMI, c) Normal-STEMI groups.

According to the results obtained as shown in Table 2 and Fig. 4, the ACS-Normal classification showed the highest performance with the proposed model. In the classification of the STEMI-Normal group, lower performance was obtained in terms of sensitivity, while higher results were obtained in other metrics. In the classification of the NSTEMI-Normal group, slightly lower performance values were obtained in general compared to the classification of the other groups, which reflects the difficulties of this class, which is also known clinically.

IV. CONCLUSIONS

Evaluating cardiac abnormalities using ECG signals is a very important field. An accurate method to detect ECG signals of individuals with ACS ensures that the correct treatment is applied to the patients. In this study, an MI classification method combining CNN and LSTM models is developed. The proposed CNN-LSTM model provided a computerized classification of STEMI, NSTEMI, and Healthy ECG signals with high performance. For ECG time series signals, the features learned from CNN were used for the LSTM approach, and successful results were obtained.

In this study, our approach, the selection of 10-second ECG samples by the structure in which clinicians usually visually interpret pathological changes in ECG, ensured compatibility with current real-time clinical applications offered by most physiological ECG monitors. In our study, the evaluation and classification of ECG changes in the 10-second time interval was similar to the real-time clinical practice routinely used by clinicians in ECG evaluation.

When similar studies in the literature on the detection of ACS from ECG signals are examined, it is seen that the majority of them analyze data divided into small segments, which positively affects the performance metrics (Table 1). It is seen that very few studies have used the entire 10-second standard 12-lead ECG data as a single data as in this study. In this study, 10-second standard 12-lead ECG recordings were evaluated as a whole without dividing into beats without selecting the lead. Based on the knowledge that leads close to each other vary in the evaluation of ACS according to the region of occurrence, all lead signals were used in the model development phase without selecting the lead in the study. In addition, NSTEMI, which is evaluated in very few studies in terms of ACS, could be classified with high success compared to both healthy controls and the STEMI group in this study. While many studies have developed algorithms based on the detection of ST changes in ECG signals, very few studies have investigated ECG changes for NSTEMI. In addition, the most important advantage of this study is that it is based on real patient data, and no ready-made data set was used. As a limitation of the research, it can be said that only MI was examined. The clinical manifestations of heart diseases are often complex and diverse. Therefore, it will be necessary to study similarly for other heart diseases to extend the use of the proposed model.

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