Research Article

Preliminary Study Based on Myocardial Infarction Classification of 12-Lead Electrocardiography Images with Deep Learning Methods

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Abstract

In contemporary medicine, the development of computer-aided diagnostic systems using Electrocardiography (ECG) signals has gained significance for the diagnosis of heart diseases. Myocardial infarction (MI) is recognized as the condition where blood flow to the heart muscle is obstructed due to blockages in coronary vessels. In this study, four deep learning approaches were employed to automatically identify different MI conditions (STEMI, NSTEMI, USAP) using images generated from 12-lead ECG signals. The utilized architectures include deep neural networks such as Visual Geometry Group-16 (VGG-16), AlexNet, Residual Neural Network (ResNet), SqueezeNet and an ensemble model composed of these networks. With the proposed method, classification was performed based on 10-second grayscale images of 12-lead ECG signals for HC-STEMI, HC-NSTEMI, HC-USAP, and NSTEMI-STEMI conditions.

According to the obtained results, the HC-STEMI group achieved the highest performance with a cross-validated 0.8237 F1 score using the AlexNet architecture.
Among the novel contributions of this study is the image-based ECG classification method that can be more easily adapted to clinical applications and the analysis of the potential use of detecting different MI conditions in clinical practices. In conclusion, this study sheds light on future research by demonstrating the significant potential of using multi-channel ECG signals in image format for MI diagnosis, paving the way for advancements in this field.

Keywords: *Myocardial infarction (MI), Electrocardiography (ECG), AlexNet, ResNet, SqueezeNet, VGG16, Majority voting*

1. Introduction

The studies aiming to interpret Electrocardiography (ECG) signals rapidly and reliably for the diagnosis of heart diseases through computer-aided diagnostic systems are rapidly increasing. Numerous cardiovascular diseases related to the functioning of the heart can be effectively detected in the pre-diagnosis process using ECG signals. Myocardial infarction (MI), commonly known as a heart attack, is a prevalent condition where the blood flow to the heart muscle is obstructed or significantly narrowed due to blockages or constrictions in coronary vessels, leading to the cessation of blood supply. In the diagnosis of MI, ECG signals serve as a valuable diagnostic tool, intensively utilized by cardiologists, providing guidance for further examinations.

Based on guidelines used in MI diagnosis, ECG signals are categorized into two groups: ST-elevation myocardial infarction (STEMI) and Non-ST-elevation myocardial infarction (NSTEMI), depending on the presence or absence of elevation in the ST segment [1,2]. While STEMI is easily diagnosed by cardiologists due to observable changes in the ECG signal, NSTEMI does not exhibit noticeable alterations, requiring physicians to monitor certain blood values and conduct more advanced tests for diagnosis when ECG signals do not show apparent changes.

In recent years, overcoming these challenges in diagnosing MI using ECG signals has involved not only extracting classical features but also deriving new features to maximize the information contained in the signals [2]. Moreover, the increasing use of deep learning and artificial intelligence applications has led to the direct application of ECG signal images to deep learning, facilitating the extraction of numerous features and classifications.

Given the fact that ECG signals are visually obtained and stored in many health centers, working with multi-channel ECG signal images emerges as a promising approach for faster, reliable, and easier automation of MI diagnosis.

Among the deep learning methods for MI detection, Convolutional Neural Networks (CNN) have been identified as the most widely used model [3]. Various studies have proposed CNN models for feature extraction from R-R intervals and R amplitudes, achieving notable accuracies [4,5,6,7].

Different approaches have been explored, including the use of CNN and GaborCNN models for classifying coronary artery disease, MI, and congestive heart failure, highlighting the potential of working with multi-channel ECG signal images [8].

Aversano et al. conducted a study involving CNN and three-band feature extraction from 12-channel ECG signals, achieving successful classification of MI potential, previously MI-experienced group, and a group with abnormal heart rhythms, along with healthy individuals [9].

Uslu et al. applied 2D-CNN to ECG wavelet scalogram images, focusing on identifying left atrial overload in patients with excessive left atrial pressure. Notably, this study achieved a 97% success rate using only Lead II derivation [10].

Most of the summarized literature studies have predominantly worked with one or a few derivations of 12-lead ECG signals, primarily utilizing open-access databases. Classical CNN approaches, as well as network structures such as Le-NET, VGG-Net, and LSTM, have been favored for classification. Additionally, these studies have often focused on working with general heart conditions, without separately considering subgroups like STEMI, NSTEMI, and USAP.

The objectives and novel contributions of this study can be summarized as follows:

• Simplifying and expediting the diagnosis of MI by working with original ECG signals obtained automatically from commercial ECG systems instead of ECG signals in the time domain. This approach eliminates the need for additional procedures and tools to acquire ECG signals from devices, as well as traditional stages and limitations of preprocessing, filtering, and feature extraction.

• Working with real datasets obtained with our research team and utilizing the images of the initial ECG signals of patients presenting to the hospital with complaints of chest pain. This allows the acquisition of a specific and real dataset for MI, aiding practical diagnosis.

• Working with all channels of 12-lead ECG signals and specifically diagnosing MI as STEMI, NSTEMI, and USAP. This approach enables the differentiation of the entire MI group with images of all channel/derivation ECG signals, separating the group without MI but with similar complaints (USAP) and healthy control (HC).

Overall, this study sheds light on the potential of using multi-channel ECG signals for MI diagnosis, paving the way for more efficient and accurate diagnostic approaches in the future.

2. Materials and Methods

2.1. Demographic Acknowledgement

The 12-lead ECG is primarily used in emergency departments for patients reporting chest pain symptoms. Identifying acute coronary syndrome patients in emergency departments is a major challenge. Today, in hospital settings, ECG recordings are usually stored as images in Picture Archiving and Communication System (PACS) using the Digital Imaging and Communications in Medicine (DICOM) format [11]. The diagnosis of acute coronary syndrome is based on a standard 12-channel ECG and this is a time-consuming task requiring specialized expertise.

In this study, 12-channel ECG signals obtained from patients who came to Erciyes University Hospital Emergency Department with chest pain were evaluated. Ethical approval for the use of patient records was obtained from Erciyes University Ethics Committee. The study was conducted on 100 record from each group for healthy control ECGs as well as ECGs diagnosed with STEMI, NSTEMI and USAP. The data set used consisted of 12-lead ECGs obtained retrospectively from Erciyes University Faculty of Medicine Hospital PACS between 2018 and 2023. For each group, the information of the 10-second standard ECG recording was retrospectively obtained from the PACS system in A4 size documents. The information in these documents is converted into png images and labeled as a document specific to the region (ROI) where only 12 channels of ECG information is available to be used in deep learning algorithms.

Within the scope of the study, for the healthy group, ECG records of people who were between the ages of 18-80, who had not had MI, who did not have cardiac disease and who did not have coronary artery disease were evaluated. For the patient groups, being between the ages of 18-80 years, ECG records of patients with chest pain or suspected acute coronary syndrome who were diagnosed with STEMI, NSTEMI or USAP were evaluated. Conditions such as left bundle branch block, paced rhythm, left ventricular hypertrophy, patients presenting with cardiac arrest and acute stroke were excluded from the study.

The disease groupings were blindly evaluated by at least two cardiologists and were formed as follows by evaluating many factors such as the presence of ST elevation or depression on the ECG of the patients, other clinical findings of the patients, and angiography results.

1. ST elevation and narrowing of angiography -STEMI
2. (ECG changes other than ST elevation) + (troponin elevated) → NSTEMI
3. (ECG changes other than ST elevation) + (troponin low) → USAP

Table 1 shows the demographic characteristics of all subjects who participated in the study.

Table 1: Demographic characteristics of participants.

		HEALTHY	STEMI	NSTEMI	USAP
Gender	Female	8	22	40	24
	Male	92	40	60	66
Age	Mean	49,03	59,53	62,83	59,64
	Std.	16,95	13,11	12,98	10,44
	Min.	18	33	26	34
	Max.	80	80	80	80

The flowchart of the conducted study is seen in Figure 1.

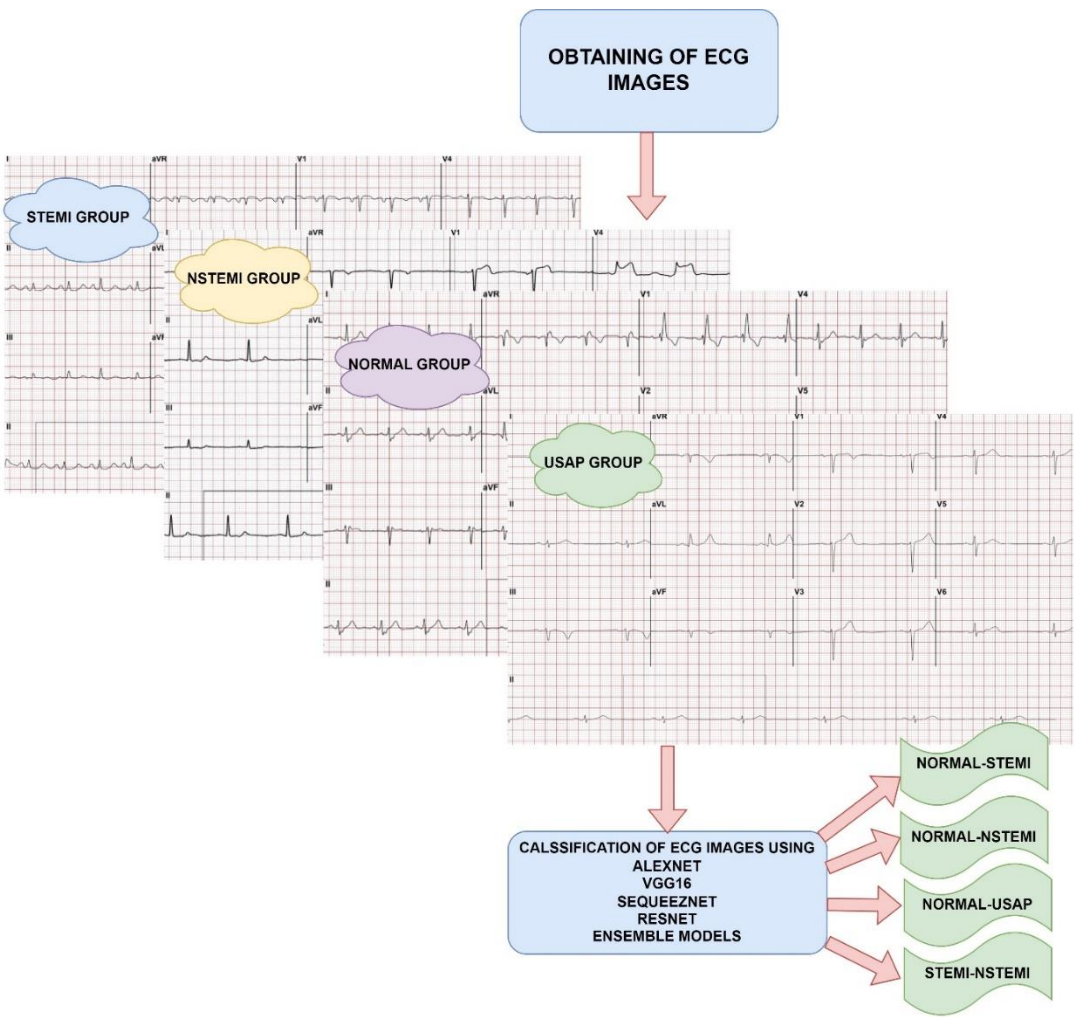


Figure 1: Flowchart of the study

2.2 Classification Of ECG Data With Deep Neural Networks

Images of 12-lead ECG signals will be used for classification. Deep learning is able to learn and make decisions based on unstructured, no features have been removed and unlabeled data. In particular, instead of producing results based only on rule sets or features obtained from the data, the deep learning approach obtains information from examples and then produces results using this information. Therefore, in the deep learning approach, the classification result is obtained by directly using the data itself instead of the features obtained from the data.

Deep Learning (DL) is a machine learning (ML) method consisting of neural networks that enables the sequential learning of data features [12]. In DL, features are learned automatically without the need for pre-feature extraction, making DL methods potentially superior to traditional ML methods [12]. CNNs are among the most commonly used models in DL.

A CNN consists of an input layer, one or more hidden layers, and an output layer. In these networks, each neuron in one layer is connected to every neuron in the previous layer, giving rise to the term "fully connected network." However, these networks may be insufficient for dealing with classification problems involving large-sized images due to many connections, leading to the adjustment of neurons with a considerable amount of weight [13, 14]. The use of numerous parameters can pose some problems. To overcome this, various hyperparameters provided by the user need to be adjusted for any signal or image classification problem in a CNN. Therefore, creating a CNN model can be a time-consuming process. To simplify this process, some well-designed pre-trained deep convolutional neural networks are available [14, 15]. These networks include classifiers with slight modifications, such as Visual Geometry Group-16 (VGG-16), AlexNet, Residual Neural Network (ResNet), and SqueezeNet. The relevant information for these classifiers is provided below.

VGG-16: VGG-16, one of the two versions of CNNs, was first proposed in 2014 [16]. The VGG-16 architecture consists of 13 convolutional layers and three fully connected layers (a total of 16 layers). The kernel sizes are fixed in this model.

AlexNet: Proposed as a CNN by Krizhevsky et al. in 2012, AlexNet's architecture includes consecutive convolutional, maximum pooling, and fully connected layers. Rectified linear unit (ReLU) is used as the activation function [17, 18]. Unlike VGG-16, the kernel sizes in this model are not fixed. AlexNet is mostly used for image classification [18].

ResNet: ResNet is a new CNN model that skips connections and layers to address the degradation problem observed in CNNs. Several ResNet types, such as ResNet-18 and ResNet-50, are used for different layer differences, catering to small and large-scale problems.

SqueezeNet: SqueezeNet, created in 2016, has a compact architecture with fewer parameters compared to other CNN models [16, 17,18,19,20,21]. It uses up to 50 times fewer parameters than AlexNet, reducing computational power requirements [22]. SqueezeNet aims to achieve good results in image classification by using fewer parameters without losing accuracy. It consists of a squeeze layer and an expand layer [16].

Majority Voting (MV): MV is a community machine learning model based on the predictions of several models about the data. In this classification model, predictions from multiple classifiers are combined to perform the classification process. This allows predictions to be made not based on the result obtained from a single model but by combining predictions from different classifier models. MV is a model that can be used in both classification and regression studies. The general working structure of the MV model is as shown in Figure 2.

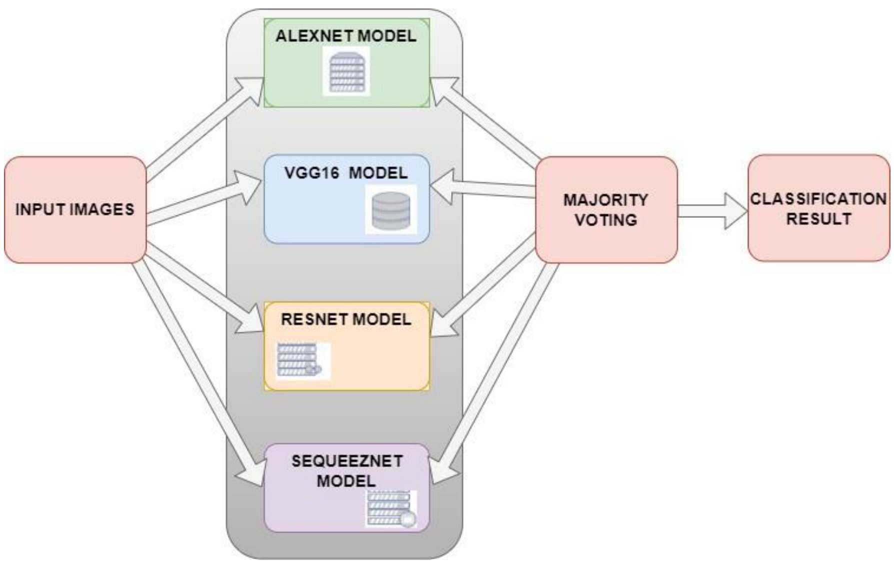


Figure 2: MT model basic working principle

2.3 Performance Parameters

This study employed the models described above during the classification phase. The k-fold cross-validation (CV) technique was applied during the classification process. In k-fold CV, the data is divided into k equal parts. In each iteration, k-1 parts are used to train the model, and the remaining k parts are used for testing the model. This process is repeated k times, and the average of the results is calculated to determine the model's performance. In this study, k was set to 5 (CV:5). According to CV:5, 20% of the data was designated for testing, and 80% for training during the classification process. After each fold, performance metrics, including accuracy, sensitivity, specificity, precision, recall, and F1-score, were calculated to evaluate the classifiers' performance (Formulas 1-6). The average of these values was used to calculate the classifiers' overall performance. The ratios of performance metrics were calculated based on the sample confusion matrix provided in Table 2 during the computation process. True positive (tp), true negative (tn), false positive (fp), and false negative (fn) rates were used in the calculation process.

$$Accuracy = \frac{tp+tn}{tp+tn+fp+fn} \times 100 \quad (1)$$

$$Sensitivity = \frac{tp}{tp+fn} \times 100 \quad (2)$$

$$Specificity = \frac{tn}{tn+fp} \times 100 \quad (3)$$

$$\text{Precision} = \frac{tp}{tp+fp} \times 100 \quad (4)$$

$$\text{Recall} = \frac{tp}{tp+fn} \times 100 \quad (5)$$

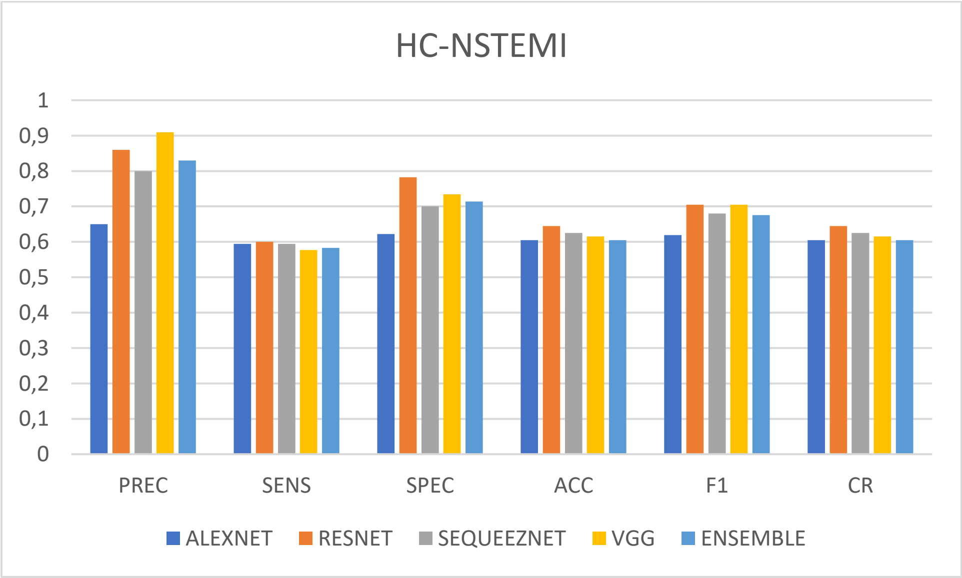
$$F1 - Score = \frac{2 \times \text{Sensitivity} \times \text{Precision}}{\text{Sensitivity} + \text{Precision}} \times 100 \quad (6)$$

Table 2: An example of confusion matrix

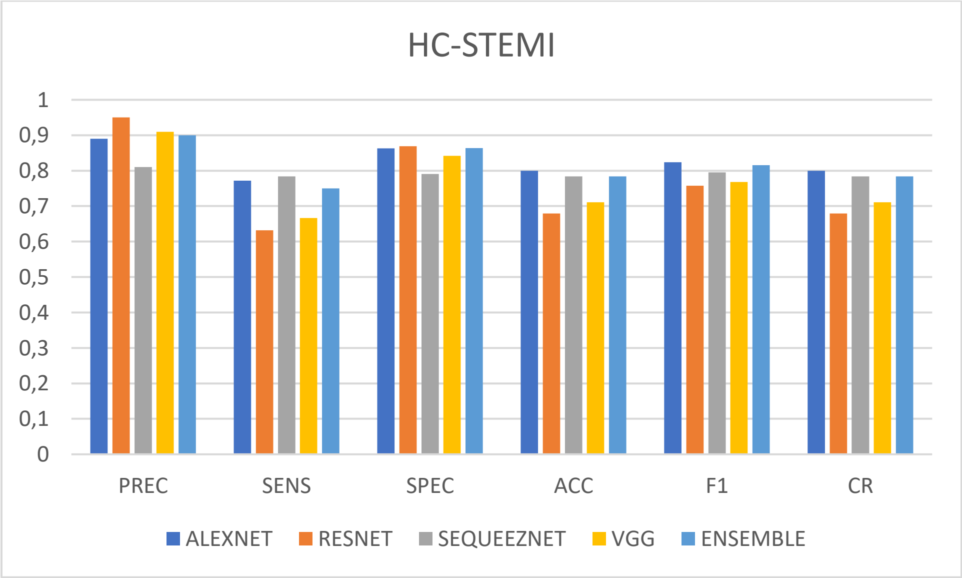
		Actual Value	
		0	1
Predicted Value	0	**TN**	**FN**
	1	**FP**	**TP**

3. Results and Discussion

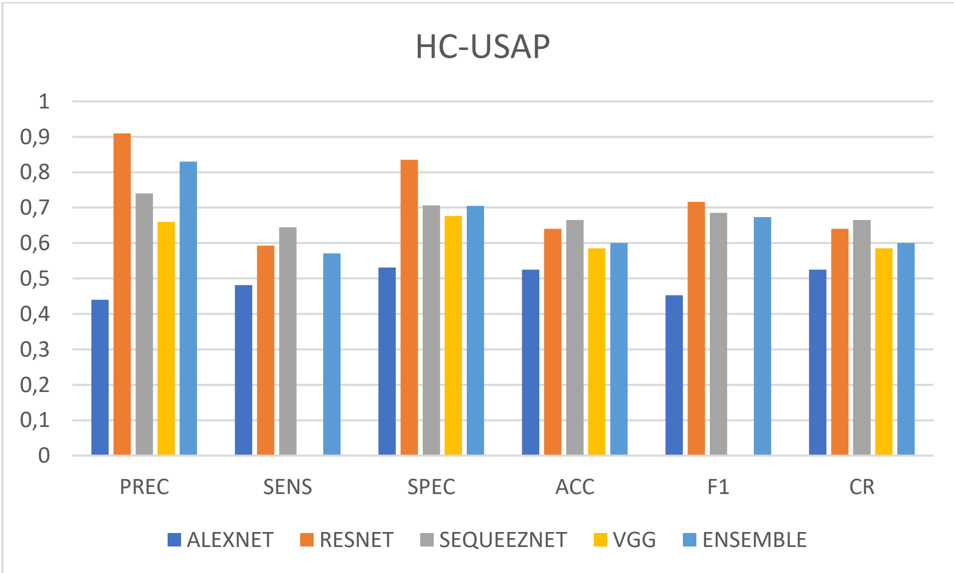
In the conducted study, ECG images were classified using a 5-fold cross-validation approach with AlexNet, VGG16, ResNet, SqueezeNet, and an ensemble method. The performance values obtained from the results are depicted in Figure 3.


HC-NSTEMI
1
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
PREC
SENS
SPEC
ACC
F1
CR
ALEXNET
RESNET
SEQUEEZNET
VGG
ENSEMBLE

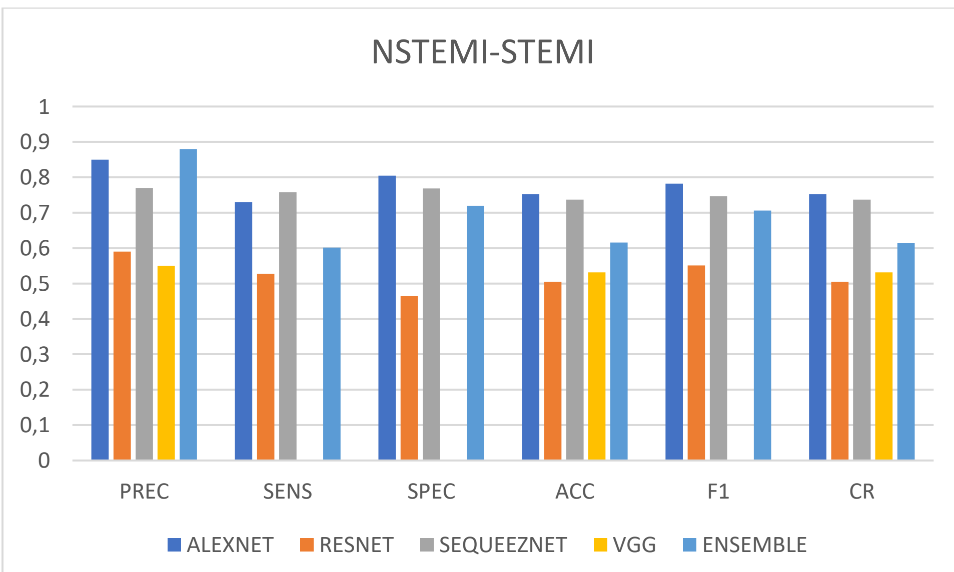
a)


HC-STEMI
1
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
PREC
SENS
SPEC
ACC
F1
CR
ALEXNET
RESNET
SEQUEEZNET
VGG
ENSEMBLE

b)



c)



d)

Figure 3: Classification performances of a) HC-NSTEMI, b) HC-STEMI, c) HC-USAP and d) NSTEMI-STEMI classes obtained from ECG images

When evaluating the obtained results, it is observed that the highest classification success in the HC-NSTEMI group was achieved using the VGG16 model, with an F1 score of 0.7045. In the HC-STEMI group, a classification performance was achieved using the AlexNet model with an F1 score of 0.8237. The highest classification performance in the HC-USAP group was obtained with the use of the ResNet model, reaching an F1 score of 0.7160. In the NSTEMI-STEMI group, the AlexNet model achieved the highest classification performance with an F1 score of 0.7821.
According to these results, it is indicated that the highest performance using 12-channel ECG images was achieved in the HC-STEMI group, with a classification rate of 80%. This success is particularly noteworthy for the AlexNet model's high performance in the HC-STEMI group. These achievements demonstrate the potential of the proposed method as an effective tool in the diagnosis of cardiovascular diseases. In the future, the method's performance could be further improved by evaluating larger patient datasets and different deep learning architectures.

4. Conclusion

In the conclusion section, an overview of the study's findings emphasizes the successful use of deep neural networks and pre-trained models in classifying ECG images, with satisfactory results achieved through different classifiers such as VGG-16, AlexNet, ResNet, SqueezeNet, and a community model formed by combining these models. The majority voting method is highlighted for its effectiveness in combining predictions from different classifiers, especially in scenarios with variations among models.
The proposed method, based on 12-lead ECG data, is discussed as a common examination method in the diagnosis of cardiovascular diseases. The text points out the advantage of using image representations of ECG signals, especially in hospital environments where signals from devices are stored as images. However, it acknowledges the disadvantage of increased computational complexity due to the large input dimensions of ECG images for deep neural networks.
The study emphasizes the importance of addressing real-time clinical validation, especially considering that the detection of cardiac abnormalities, such as myocardial infarction (MI), remains a time-consuming process in routine ECG signal interpretation by experts. The proposed method introduces four deep learning approaches for the automatic diagnosis of different MI conditions using images derived from multi-channel ECG signals. The potential advantages of the method in reducing delays in the treatment process for patients with critical conditions are discussed.
Despite the extensive literature on ECG classification for various cardiac diseases, the majority of existing systems focus on distinguishing STEMI from HC healthy data, largely ignoring different categories of MI groups. In this study, four classes (HC, STMI,

NSTEMI, and USAP) are jointly defined to address real challenges in diagnosis. The methodology is evaluated on a real ECG dataset manually categorized and obtained from Erciyes University Medical Faculty Hospital.

In conclusion, the study proposes a novel and potentially improvable perspective on the automatic diagnosis of MI from images of multi-channel ECG signals. The method shows significant potential for MI diagnosis using image representations of multi-channel signals and can be applied in real-time processes. The performance of the proposed method can be enhanced through innovations in different deep learning architectures or combination configurations. Additionally, the method has the potential to be generalized for the evaluation of different cardiac diseases using images generated from ECG signals. Future research is aimed at increasing the number of patients throughout the project, and further investigations and reviews will be conducted to enhance the automatic diagnosis of MI from ECG signal images.

5. Acknowledge

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