AUTOMATIC ARRHYTHMIA CLASSIFICATION FROM ELECTROCARDIOGRAM MEASUREMENTS WITH DEEP LEARNING

DERİN ÖĞRENME İLE ELEKTROKARDİYOGRAM ÖLÇÜMLERİNDEN OTOMATİK ARİTMİ SINIFLANDIRMA

BERKCAN YURTSEVER

PROF. DR. EBRU AKÇAPINAR SEZER
Supervisor

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ABSTRACT

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Berkcan YURTSEVER

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Supervisor: Prof. Dr. Ebru AKÇAPINAR SEZER
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ECG signals have an important place in detecting arrhythmias. Arrhythmias are irregular heartbeats. One of the most popular studies in this field is the classification of arrhythmias with artificial neural networks. In the thesis study, a classification study of arrhythmias was carried out with artificial neural networks using ECG lead signals. In this way, it can be determined directly whether there is an arrhythmia or not as soon as an ECG recording is taken.

The dataset used in the study was obtained by combining the ECG recordings in the PTB-XL and Chapman datasets. The types and numbers of arrhythmias in each data set vary. When working on a single data set, trained models will be successful in classifying certain arrhythmias. However, it will fail to classify arrhythmias that are not included in the dataset. To avoid this problem, instead of working on a single data set, two different data sets were combined and a common data set was studied. Thus, models with general success in classifying arrhythmias were obtained.

More than one arrhythmia can be found in an ECG recording. Since an ECG recording may contain more than one arrhythmia, a threshold value approach was used to classify multi-label ECG recordings. Thus, the trained models were able to detect multiple arrhythmias in ECG recordings.

An ECG recording may contain no arrhythmias. The 'no arrhythmia' class has been defined to classify ECG recordings that do not contain any arrhythmia. Defining the 'no arrhythmia' class is a new approach. By defining the 'no arrhythmia' class, it can be determined whether the ECG recordings contain any arrhythmia. In ECG recordings containing arrhythmia, more than one arrhythmia can be detected with the threshold value approach.

We trained SE-ResNet34 and FCN artificial neural networks to classify arrhythmias detected through ECG recordings. The Squeeze and Excitation (SE) layer enable the network to perform dynamic channel-wise feature recalibration. One-dimensional convolutional network was used for feature extraction from 12-lead ECG recordings in the dataset. The convolutional network used is 34-layer ResNet.

By using the weight function, less weight was given to arrhythmias that occurred more frequently in the data set, and more weight was given to arrhythmias that occurred less frequently. The weight function is given as a parameter while training the model. The studies were conducted for 5, 10, and 15 classes of arrhythmia entities. Training the model on 5 arrhythmias takes less time than on 10 and 15 arrhythmias, since it contains fewer neurons in terms of running time.

Changing the threshold value greatly affects the success of the model. While many arrhythmia classes occur at low threshold values, only a single arrhythmia class occurs at high threshold values. The reason for this is that if no arrhythmia exceeds the threshold value, the arrhythmia with the highest prediction score is considered as the output of the model.

In the FCN model, when working with 5, 10 or 15 arrhythmias, the best results were always obtained when the threshold value was 55%. In the ResNet model, the best results were obtained at 35% threshold values when working with 5 arrhythmias, and at 10% threshold values when working with 10 and 15 arrhythmias.

In the thesis study, it was seen that the FCN model was more successful in detecting arrhythmias than the ResNet model.

In the models created, arrhythmias can be detected with success rates ranging from 60 percent to 90 percent. The current study may help cardiologists make a diagnosis by preventing misinterpretation of ECG signals.

Keywords: Electrocardiogram (ECG), Classification, Deep Learning, Arrhythmia.

ÖZET

DERİN ÖĞRENME İLE ELEKTROKARDİYOGRAM ÖLÇÜMLERİNDEN OTOMATİK ARİTMİ SINIFLANDIRMA

Berkcan YURTSEVER

Yüksek Lisans, Bilgisayar Mühendisliği
Tez Danışmanı: Prof. Dr. Ebru AKÇAPINAR SEZER
Haziran 2024, 61 sayfa

EKG sinyalleri aritmilerin tespitinde önemli bir yere sahiptir. Aritmiler düzensiz kalp atışlarıdır. Bu alanda yapılan en popüler çalışmalardan biri de aritmilerin yapay sinir ağları ile sınıflandırılmasıdır. Tez çalışmasında EKG sinyalleri kullanılarak yapay sinir ağları ile aritmilerin sınıflandırılma çalışması yapılmıştır. Bu sayede EKG kaydı alınır alınmaz aritmi olup olmadığı doğrudan tespit edilebilmektedir.

Çalışmada kullanılan veri kümesi, PTB-XL ve Chapman veri kümelerindeki EKG kayıtlarının birleştirilmesiyle elde edilmiştir. Her veri kümesindeki aritmilerin türleri ve sayıları farklılık gösterir. Tek bir veri kümesi üzerinde çalışırken, eğitilmiş modeller belirli aritmileri sınıflandırmada başarılı olabilmektedir. Ancak veri kümesinde yer almayan aritmileri sınıflandırmada başarısız olabilmektedir. Bu sorunu önlemek için tek bir veri kümesi üzerinde çalışmak yerine iki farklı veri kümesi birleştirilerek ortak bir veri kümesi üzerinde çalışıldı. Böylece aritmilerin sınıflandırılmasında genel başarıya sahip modeller elde edilmiştir.

Bir EKG kaydında birden fazla aritmi bulunabilir. Bir EKG kaydı birden fazla aritmi içerebileceğinden, çok etiketli EKG kayıtlarının sınıflandırılmasında eşik değer yaklaşımı kullanılmıştır. Böylece eğitilen modeller, EKG kayıtlarında yer alan çoklu aritmileri tespit edebilmektedir.

Bir EKG kaydında herhangi bir aritmi bulunmayadabilir. 'Aritmi yok' sınıfı, herhangi bir aritmi içermeyen EKG kayıtlarını sınıflandırmak için tanımlanmıştır. 'Aritmi yok' sınıfının tanımlanması yeni bir yaklaşımdır. 'Aritmi yok' sınıfı tanımlanarak EKG kayıtlarının herhangi bir aritmi içerip içermediği belirlenebilir. Aritmi içeren EKG kayıtlarında eşik değer yaklaşımıyla birden fazla aritmi tespit edilebilmektedir.

EKG kayıtlarından tespit edilen aritmileri sınıflandırmak için SE-ResNet34 ve FCN yapay sinir ağları eğitildi. Sıkıştırma ve Uyarma (SE) katmanı, ağın dinamik kanal bazında özellik yeniden kalibrasyonu gerçekleştirmesini sağlar. Veri setindeki 12 derivasyonlu EKG kayıtlarından özellik çıkarımı için tek boyutlu evrişimsel ağ kullanıldı. Kullanılan evrişimli ağ 34 katmanlı ResNet'tir.

Ağırlık fonksiyonu kullanılarak veri setinde daha sık meydana gelen aritmilere daha az, daha az sıklıkta meydana gelen aritmilere ise daha fazla ağırlık verilmiştir. Model eğitilirken ağırlık fonksiyonu parametre olarak verilmektedir. Çalışmalar 5, 10 ve 15. sınıf aritmi varlıkları için yürütüldü. Modeli 5 aritmi üzerinde eğitmek, çalışma süresi bakımından daha az nöron içerdiğinden, 10 ve 15 aritmiye göre daha az zaman almaktadır.

Eşik değerinin değiştirilmesi modelin başarısını büyük ölçüde etkilemektedir. Düşük eşik değerlerinde birçok aritmi sınıflandırılırken, yüksek eşik değerlerinde yalnızca tek bir aritmi sınıflandırılmaktadır. Bunun nedeni eşik değerini aşan herhangi bir aritmi olmaması durumunda tahmin puanı en yüksek olan aritminin modelin çıktısı olarak dikkate alınmasıdır.

FCN modelinde 5, 10 veya 15 aritmi ile çalışırken en iyi sonuçlar her zaman eşik değeri %55 olduğunda elde edilmiştir. ResNet modelinde en iyi sonuçlar 5 aritmi ile çalışırken %35 eşik değerlerinde, 10 ve 15 aritmi ile çalışırken ise %10 eşik değerlerinde elde edilmiştir.

Tez çalışmasında FCN modelinin aritmileri tespit etmede ResNet modeline göre daha başarılı olduğu görülmüştür.

Oluşturulan modellerde yüzde 60 ile yüzde 90 arasında değişen başarı oranlarıyla aritmiler tespit edilebilmektedir. Bu çalışma, EKG sinyallerinin yanlış yorumlanmasını önleyerek kardiyologların tanı koymasına yardımcı olabilir.

Anahtar Kelimeler: Elektrokardiyogram (EKG), Sınıflandırma, Derin Öğrenme, Aritmi.

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SYMBOLS AND ABBREVIATIONS

Abbreviations

CT	Clinical Terms
DNN	Deep Neural Networks
ECG	Electrocardiogram
FCN	Fully Connected Network
FN	False Negative
FP	False Positive
ResNet	Residual Network
TN	True Negative
TP	True Positive
SE-ResNet	Squeezee and Excitation Residual Network
SNOMED-CT	Systematized Nomenclature of Medicine - Clinical Terms

1. INTRODUCTION

Electrocardiogram (ECG or EKG) is a recording of the heart's electrical activity through repeated cardiac cycles. Thanks to electrodes placed on the body, the electrical activity of the heart is measured in a timeline. These electrodes placed on the body detect small electrical changes that occur in the heart muscle during each cardiac cycle.

ECG signals consist of 12 lead signals. Ten different electrodes are placed on the patient's legs and chest to record the patient's ECG. In this process, the electrical activity of the heart is recorded from 12 different angles. Recordings are usually 10 seconds long. Each of the 12 different recorded angles represents a separate lead signal. With this method, the electrical activity of the heart is recorded in each cardiac cycle [1].

Arrhythmias are irregular heartbeats. Arrhythmias indicate a problem with the heart's rhythm or speed. The heart may beat too fast, too slowly, or in an irregular rhythm.

Of course, it is very normal for the heart to beat too fast or too slow during times of rest or physical activity. However, irregular rhythm disorders in the heart indicate arrhythmias.

Arrhythmias can be detected and treated. Arrhythmias, if left untreated, can damage the brain and other organs, especially the heart. This may result in stroke, cardiac arrest or heart failure [2]. The main way to detect arrhythmias is ECG recordings. The movements of the heart can be monitored and recorded with ECG recordings. The ECG recording showing the heart rhythm of a patient with arrhythmia will be different from the ECG recording of a patient with a healthy heart. Thus, arrhythmias can be detected by cardiologists. However, the fact that there are many arrhythmias and some arrhythmias are seen in fewer patients than others makes it difficult to detect arrhythmias.

12-lead ECG signals play a critical role in detecting arrhythmias and heart-related disorders. Early detection and classification of arrhythmias is very important for successful treatment.

While some arrhythmias are common, some arrhythmias are rare. For example, "sinus bradycardia" appears common, while "left ventricular hyperthrophy" appears rare. This makes it difficult to classify arrhythmias.

Arrhythmias can be classified with artificial neural networks. Before the development of artificial neural networks, there were arrhythmia classification studies using machine learning methods [51]. Machine learning methods such as SVN and genetic algorithm were used in this regard. In addition to these studies, noise reduction studies were also carried out in ECG recordings to make it easier for cardiologists to classify arrhythmias [52].

There are more than 100 types of arrhythmias. If no artificial intelligence application is used, it is entirely up to the cardiologist to detect arrhythmia from ECG records. Here, an unintentional incorrect classification may occur or an existing arrhythmia may be overlooked. To avoid this problem, artificial neural networks are trained with ECG signals.

Since there are different types and numbers of arrhythmias in each data set, a common data set was obtained by combining two different data sets. Thus, instead of designing a model that is successful in classifying specific arrhythmias, a model that is successful in classifying arrhythmias in general has been designed.

ECG recordings may contain more than one arrhythmia. However, no arrhythmia may be involved. The 'no arrhythmia' class was defined to classify ECG recordings that do not contain any arrhythmia. 'No arrhythmia' is a new approach. A threshold value approach was used to classify ECG recordings containing multiple arrhythmias. Arrhythmias exceeding the threshold value are the outputs of the model.

FCN and ResNet models were used as models. In general, the FCN model was more successful than the ResNet model in all conditions. Multi-label training - single-label output, multi-label training - multi-label output approaches have been studied. Accordingly, a success rate of 80% to 90% was achieved in the multi-label training single-label output approach. This approach is extremely successful if the ECG recording contains a single arrhythmia. However, if there is more than one arrhythmia in the ECG recording, this method can detect only one of them. At this stage, the multi-label training - multi-label output approach is used. In this method, when trying to detect all arrhythmias in the ECG recording, the success rate drops to the range of 48%-65%.

This thesis aims to classify arrhythmias with artificial neural networks and thus help cardiologists. Thanks to the thesis study, possible arrhythmia types can be reported as soon as an ECG recording is taken. This can be extremely helpful in arrhythmia classification work, which is entirely the job of cardiologists.

2. BACKGROUND OVERVIEW

In this section, ECG signals, arrhythmias, SNOMED-CT, artificial neural networks, feed forward neural network, convolutional neural network (CNN), residual network (ResNet) and fully connected network (FCN) are explained in detail.

2.1. ECG Signals

An example of 12-lead ECG signal can be seen in Figure 2.1. When Figure 2.1 is divided in half, it can be seen that there are 6 different derivation signals (I, II, III, aVR, aVL, aVF) on the left side and 6 different derivation signals (v1, v2, v3, v4, v5, v6) on the right side.

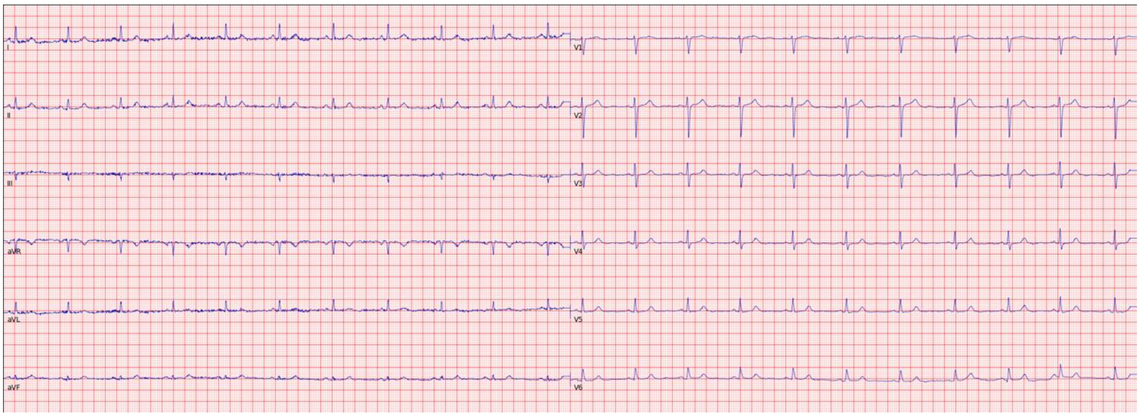

Figure 2.1 Sample ECG Recording

The representation in Figure 2.1 is a standard representation. ECG recordings can be viewed this way in many places. The ECG recording shown is a 10-second recording. Each rise, fall and sudden jump in the ECG recording has a meaning. These meanings can be seen in Figure 2.2 when the ECG recording is examined more closely.

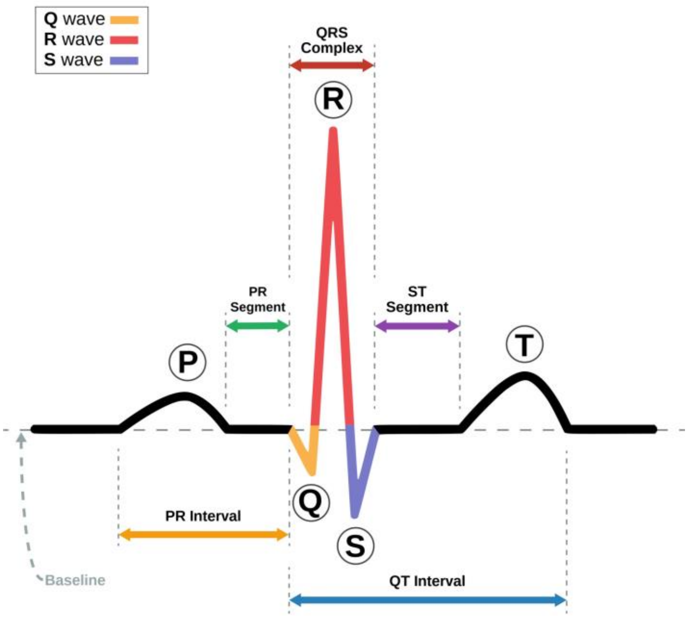

Figure 2.2 Parts of ECG [3]

As stated in Figure 2.3, 10 electrodes must be placed on the patient's body in order to record a 12-lead ECG. The locations of these electrodes and the lead signals they represent can be seen in Figure 2.3.

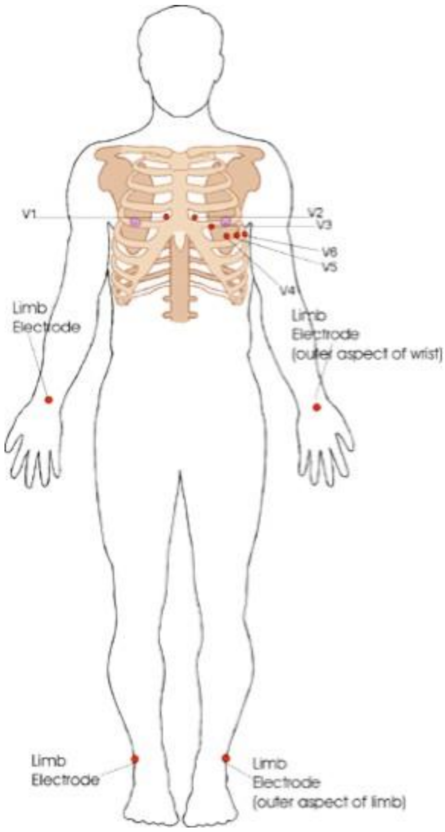

Figure 2.3 Distribution of Electrodes in The Body [4]

2.2. Arrhythmias

Arrhythmias, as explained in Section 1, are disorders that indicate a problem in the rhythm of the heart. Arrhythmias can be detected with ECG devices that examine the functioning of the heart over time [5].

Arrhythmias may be noticed by patients with various symptoms before being detected by ECG signals. Arrhythmias have similar symptoms. Popular arrhythmias seen in arrhythmia disorders can be listed as follows [6]:

- Chest Pain
- Difficulty when exercising, getting tired easily
- Continuously feeling of low energy
- Heart palpitations, feeling that the heart is beating too fast or too slow
- Shortness of breath
- Instant sweating without any reason such as exercise

Although most arrhythmias are harmless, some can have a profound impact on life. For example, ventricular fibrillation or ventricular tachycardia can cause fainting and sudden death.

The normal heart rhythm for adults is between 60 and 100 beats per minute. Normal heart rhythm in professional athletes may be below 60.

Generally, arrhythmias are divided into 5 main categories. This distinction is determined by the heart rate and where in the heart there is discomfort. Arrhythmia groups can be summarized as follows [7]:

1. Tachycardia: It is a fast heart rhythm. Causes the heart to beat more than 100 beats per minute.
2. Bradycardia: It is a slow heart rhythm. Causes the heart to beat less than 60 beats per minute.
3. Premature Heartbeat: It is an occasional extra heartbeat. It is usually harmless and does not cause symptoms. However, premature heartbeat can be dangerous if the patient already has heart disease.
4. Supraventricular Arrhythmias: These are tachycardias. It occurs in special tissue that transmits electrical signals from the atria to the ventricles.
5. Ventricular Arrhythmias: These are tachycardias that start in the lower chambers of the heart. They can be life-threatening

Atrial Fibrillation (AF) is the most common irregular heart rhythm that causes the atria to contract abnormally [8]. The most important and feared side effect is that it paves the way for clots to form in the heart, and these clots break off and travel to different parts of the body (especially the brain) and cause serious problems. Figure 2.4 shows a 12-lead ECG recording of atrial fibrillation arrhythmia as an example.

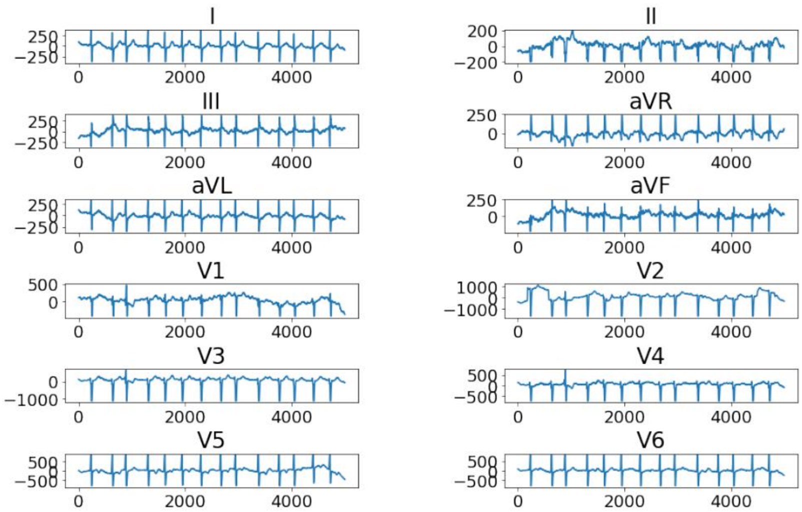

Figure 2.4 Example of 12-lead ECG Recording of Atrial Fibrillation Arrhythmia [9]

The most popular method for detecting arrhythmias is ECG devices. However, ECG devices are not the only method. Arrhythmias can be detected with different devices and methods. Methods used to detect arrhythmias other than ECG signals can be summarized as follows [10]:

- Chest X-ray: This method takes pictures of the heart using radiation. In this way, it can be seen whether there is an enlargement of the heart.
- Coronary Angiogram: X-rays are used to view blood flow in the heart arteries.
- Echocardiogram (echo): Using sound waves, images are taken from various parts of the chest and a detailed picture of the heart is created.

2.3. SNOMED-CT

SNOMED-CT is an international terminology used in the healthcare industry [11]. Each arrhythmia has a SNOMED CT code. Examples of arrhythmia types, their abbreviations and SNOMED-CT codes can be seen in Table 2.1.

Table 2.1 SNOMED-CT Codes of Some Arrhythmias

Dx	Abbreviation	SNOMED-CT Code
1st degree av block	IAVB	270492004
Atrial fibrillation	AF	164889003
Atrial flutter	AFL	164890007
Bradycardia	Brady	426627000

2.4. Artificial Neural Networks

Artificial neural networks are similar to biological neural networks in their working method. Just like biological neural networks, neurons in artificial neural networks are connected to each other and data is transferred between neurons in this connection [12]. Artificial neural networks always have an input layer and an output layer. The layer in between is called the hidden layer. The Hidden Layer does not have to be present in artificial neural networks. However, it can also be found in multiple layers.

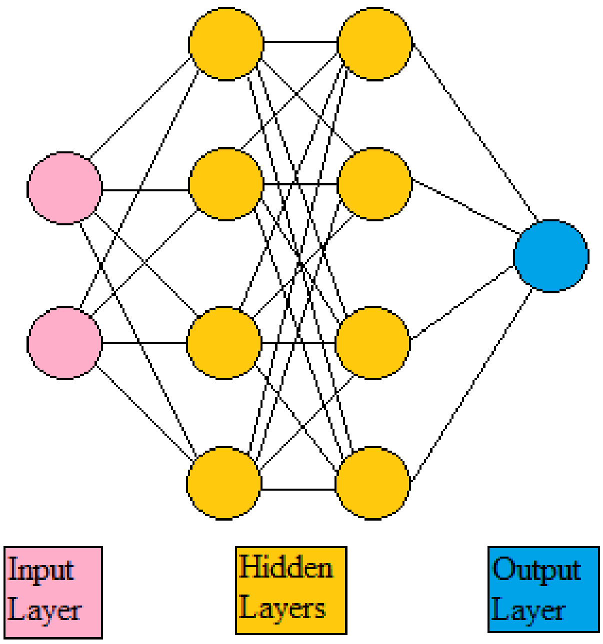

Figure 2.5 Sample Architecture of Artificial Neural Network

There are many different types of neural networks. ResNet and FCN models were used in the thesis study. These definitions are explained because the basis of the ResNet model is Convolutional Layer, and the basis of FCN model is feedforward neural networks.

2.5 Feedforward Neural Network

Feedforward networks are one of the simplest networks among artificial neural networks [13]. In this network model, data travels only forward from each layer to the next layer. No input is given to the previous layer in any way. There is no cycle in this model. Feed-forward artificial neural networks were the first artificial neural networks invented [14].

The operation of feed-forward artificial neural networks is extremely simple. It consists of only two stages. Feedforward phase and backpropagation phase.

- Feedforward Phase: In this phase, data propagates forward in the input layer. The weighted sum of the inputs is calculated and passed through an activation function. This process is done in each hidden layer. This process continues until it reaches the output layer. A prediction is made when the data reaches the output layer from the input layer.
- Backpropagation Phase: Error is calculated when the prediction process is performed. For this, the difference between the predicted result and the expected result is calculated. The weights in the networks are adjusted to reduce the error from the output layer to the input layer.

The feed-forward artificial neural network structure can be seen in Figure 2.6. Since it is a feed-forward network structure, arrow symbols always move forward.

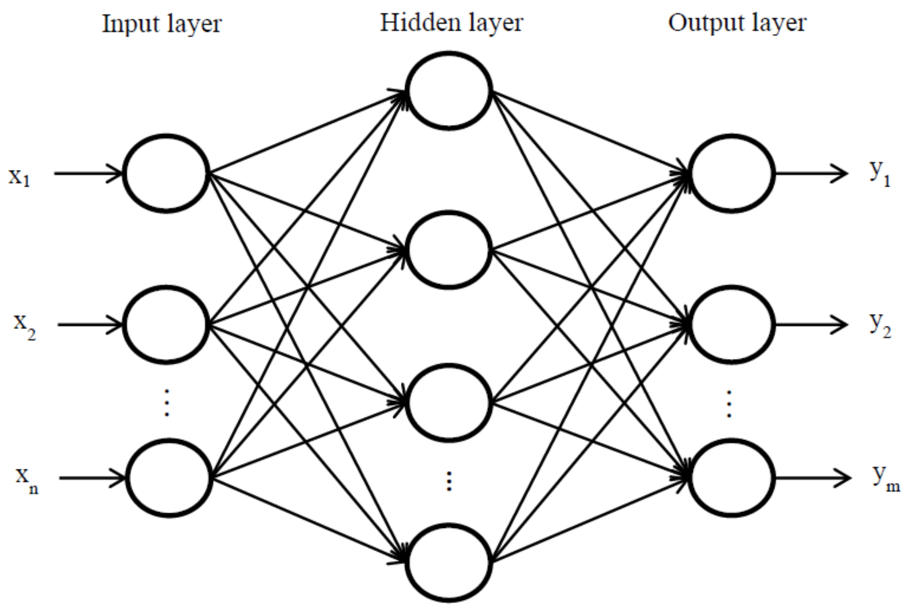

Figure 2.6 The Structure of Feed Forward Neural Network [15]

2.6. Convolutional Neural Network (CNN)

Convolutional neural networks are generally used in image classification and object identification studies.

There are 3 main layers in convolutional neural networks [16]:

- Convolutional Layer
- Pooling Layer
- Fully Connected Layer

Convolutional layer is the first layer of CNN networks. After the convolutional layer, a convolutional layer may come again or the pooling layer comes [17]. The fully connected layer is the last layer of CNN networks. With each additional layer, the complexity of the network increases.

The CNN network structure can be seen in Figure 2.7.

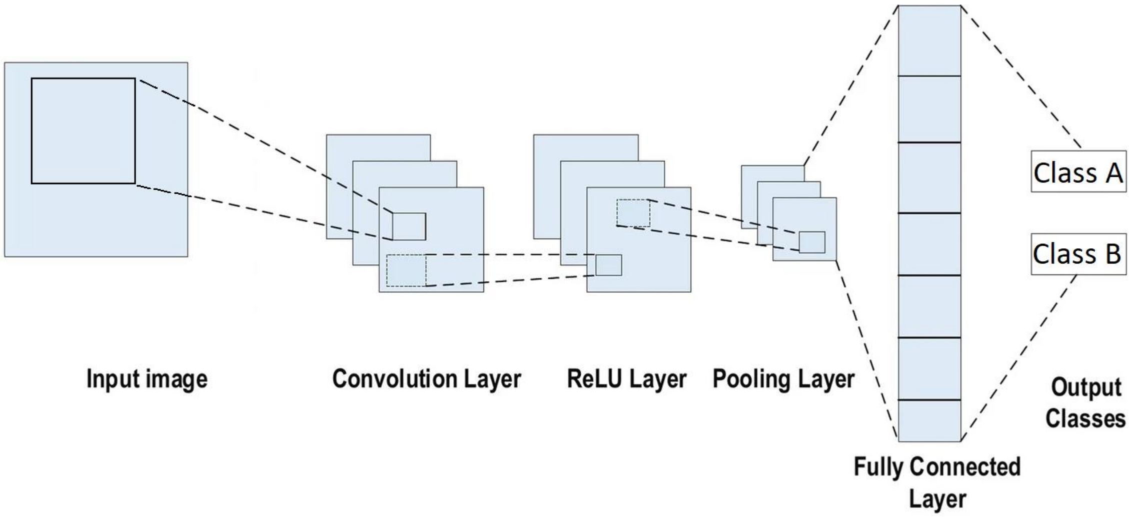

Figure 2.7 CNN Architecture

2.6.1. Convolutional Layer

The convolutional layer forms the basis of CNN networks and most of the calculations are done in this layer [18]. It takes very few parameters. These are input data, filter and feature map. By adding additional convolutional layers, the complexity of the model can be increased, allowing the model to learn smaller parts [19].

The convolution layer can be one-dimensional, two-dimensional or three-dimensional (1D, 2D or 3D). The only difference between these convolution layers is the shape of the input space. The shape of the convolution layer is determined according to the subject to be studied. For example, a one-dimensional convolution layer can be used in a study on audio files, a two-dimensional convolution layer can be used in a study on images, and a three-dimensional convolution layer can be used in a study on video.

In the thesis study, ResNet model was used and one-dimensional convolution layer was preferred as the convolution layer. This is due to the fact that ECG signals contain one-dimensional numerical data depending on time.

2.6.2 Pooling Layer

Dimension reduction is achieved with pooling layers. Similar to the convolutional layer, the entire input is scanned with the filter. However, there is no weight in the pooling layer. Instead, the output array is obtained using an aggregate function. There are two main types of pooling [20]:

- Max Pooling: The largest data in the input data to which the filter is applied is produced as output. The max pooling method is used more frequently than the average pooling method.

- Average Pooling: The average of the input data to which the filter is applied is produced as output.

2.7. Residual Network (ResNet)

A deep learning network with more than 100 layers can theoretically be designed. However, it is difficult to train. Here, ResNet allows very deep networks to be trained efficiently. When there are too many layers, data is lost in the following layers due to gradient descent, which gradually slows down. This situation is also called the Vanishing Gradient problem. ResNet uses shortcuts to solve this problem [21]. Jumping from one layer to another is achieved with a shortcut. ResNet architecture can be seen in Figure 2.8.

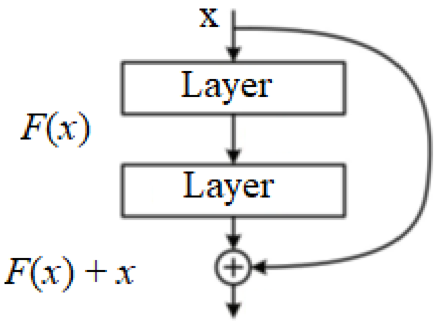

Figure 2.8 Residual Network

ResNet34, ResNet50 and ResNet101 are popular ResNet models used [22]. The numbers at the end of the model name indicate how many layers there are in that model. With the ResNet architecture, deep neural networks containing many layers can be trained without increasing the training error rate [23]. The symbol X in Figure 2.8 represents the output value from the neuron in the previous layer.

2.8. Fully Connected Network (FCN)

Neural networks consisting of multiple fully connected layers are called deep neural networks [24]. Fully Connected Deep Network consists of fully connected layers. Here, there is a relationship between any neuron in a layer and all the neurons in the previous layer. The fully connected layer can be seen in Figure 2.9.

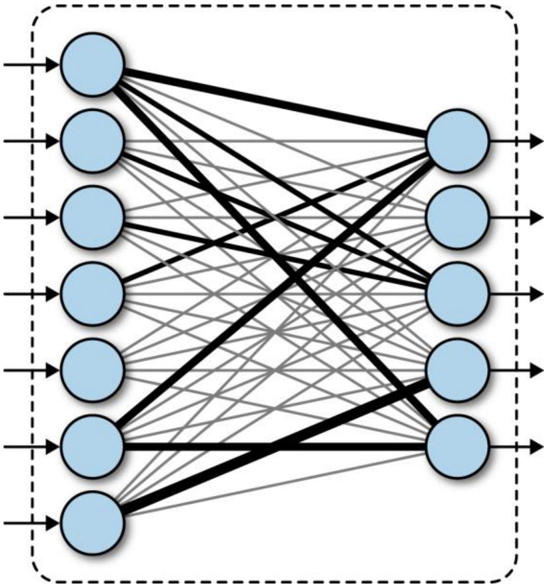

Figure 2.9 A fully connected layer in a deep network [25]

The fully connected network obtained by using fully connected layers can be seen in Figure 2.10.

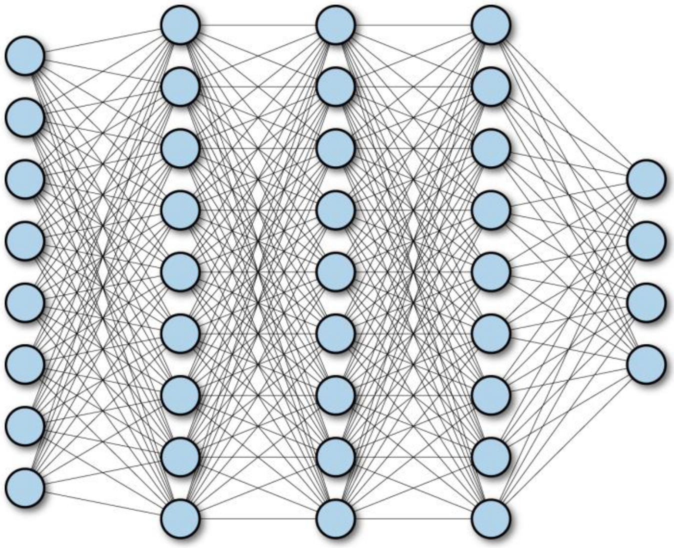

Figure 2.10 A multilayer deep fully connected network [25]

2.9. Output Layer Activation Function

The last layer of artificial neural networks includes the activation function. The choice of activation function directly affects model success [26]. How to choose the activation function in the output layer depends on the category of the study. Sigmoid and softmax functions are frequently used in classification studies [27]. If a regression study is to be performed, the linear activation function is used [28]. Because values are unbounded.

Since the classification study was carried out in the thesis study, sigmoid and softmax activation functions were used.
Sigmoid and softmax functions used in classification studies can be seen in Figure 2.11 and Figure 2.12.

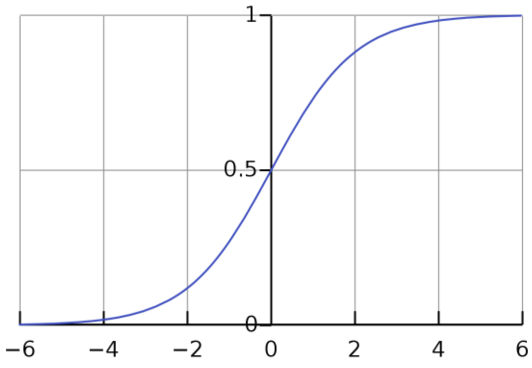

Figure 2.11 Sigmoid Function

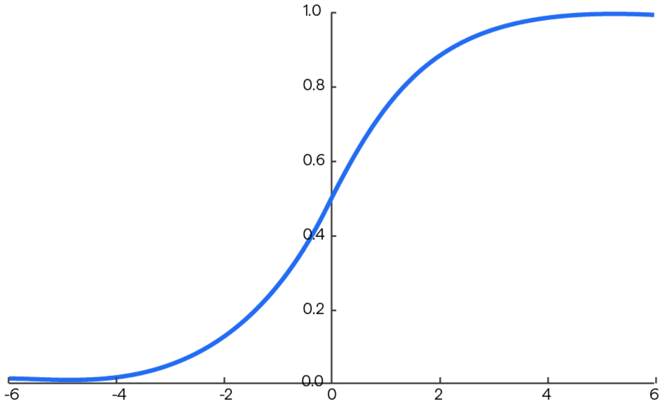

Figure 2.12 Softmax Function

The linear activation function used in regression studies can be seen in Figure 2.13.

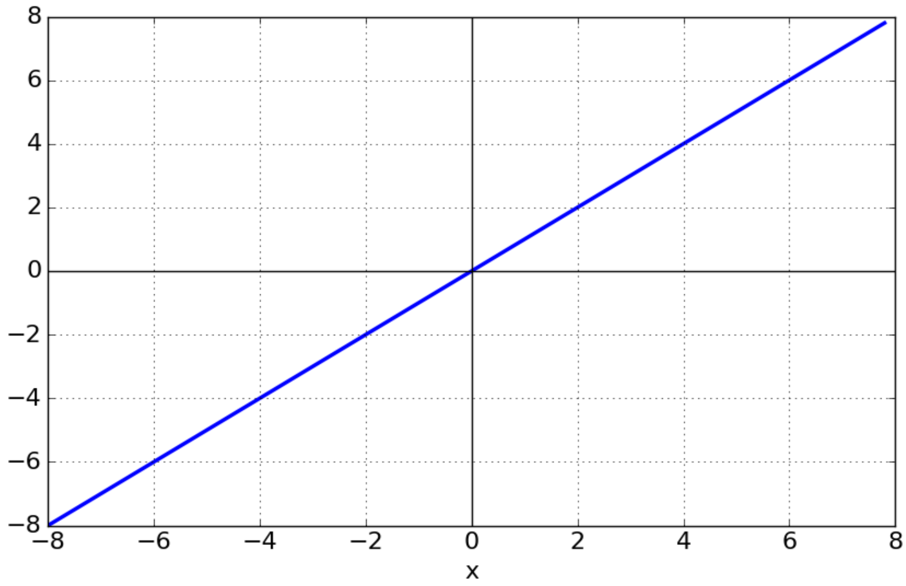

Figure 2.13 Linear Function

2.10. Confusion Matrix

Confusion matrix is a table used to evaluate the success of the model on the data set. Many inferences can be made about the success of the model just by looking at the confusion matrix. Which classes the model is successful in classifying and which classes it is unsuccessful in classifying can be determined from the confusion matrix table.

For example, when 5 different arrhythmias are studied, the confusion matrix can be seen in Table 2.2.

Table 2.2 Example Of 5 Arryhthmia Confusion Matrix

	Predicted Label					
True Label		MI	TAb	LAD	SB	SNR
	MI	34	11	20	10	3
	TAb	5	68	12	4	2
	LAD	12	24	70	18	11
	SB	7	17	3	60	12
	SNR	11	3	15	20	55

Actual classes are on the left side of Table 2.2, and estimated classes are on the top side. Accordingly, 34 ECG records containing the MI class were classified as MI. 11 ECG records containing the MI class were classified as TAb. The ratio of the sum of the numbers on the diagonal to the entire table gives the success rate.

What has been explained so far is the standard confusion matrix frequently used in machine learning methods. If a data has more than one type at the same time, then the standard confusion matrix cannot be used. For example, if an ECG recording has both LAD and MI arrhythmia types, then the standard confusion matrix is not used. Because it is correct to classify that ECG recording as either MI or LAD.

This situation creates a multiclass confusion matrix. If the data in the dataset can have more than one type at the same time, multiclass confusion matrix is used. Multiclass confusion matrix is a type-based standard confusion matrix.

For example, in the study of classifying 5 different arrhythmia types, 5 different confusion matrices are defined because each ECG record may contain more than one arrhythmia type. In each confusion matrix, it is observed whether the arrhythmia class to which it belongs is classified correctly.

As an example, in Table 2.3, the confusion matrix of a species in a multi-label environment can be seen.

Table 2.3 Confusion Matrix of MI Arrhythmia Type in Multi-Label Environment

	Predicted Label		
True Label		NOT_MI	MI
	NOT_MI	50	6
	MI	5	70

As can be seen from Table 2.3, in a multi-label environment, the confusion matrix for each class is calculated in 2x2 size. Thus, it can be seen from the confusion matrix table whether the class is classified correctly or not.

In the thesis study, multi-label confusion matrix was used to evaluate model performance in multi-label training, multi-label output studies, since ECG recordings may contain more than one type of arrhythmia.

3. RELATED WORK

Classifying and detecting arrhythmias with artificial neural networks can help doctors interpret ECG recordings. Over the past 10 years, many traditional machine learning techniques have been used to interpret ECG recordings containing 12 lead signals and diagnose heart diseases [29, 30]. However, since artificial neural networks can achieve a higher success rate than traditional machine learning techniques, studies on this subject have increased in the literature in the last five years. The majority of studies have potential for more accurate classification of arrhythmias [31, 32]. It is appropriate to use deep neural networks consisting of multiple processing layers to interpret ECG signals [33]. Because each layer can learn more abstract and higher-level representations of the input data. It is seen that LSTM and CNN network structures are frequently used in arrhythmia classification studies. As a result of this situation, ECG signals can be interpreted with deep neural networks. For this reason, there are studies in the literature to integrate the features of domain knowledge into artificial neural networks to achieve a higher success rate [34, 35].

It seems that artificial neural networks were not widely used in arrhythmia classification studies before 2015. It is seen that SVM, KNN and genetic algorithm are used in classification studies [51, 53]. However, different approaches have been applied to detect arrhythmias. In 1991, noise reduction studies were carried out by applying an adaptive filter to ECG signals [52]. This method has been especially applied to detect certain arrhythmias. As of 2015, studies on arrhythmia detection of artificial neural networks have increased. In an article published in 2022, it is seen that arrhythmia classification studies were carried out with data obtained from IoT devices [54].

The lack of sufficient ECG recording data and the fact that the arrhythmias in these ECG recordings are not well classified make it difficult to develop automatic interpretation algorithms for 12-lead ECGs [36]. Most previous studies in the literature have studied specific arrhythmias on a limited number of patients in relatively homogeneous data sets. These models perform well on the training dataset but not on the external testing set [37, 40]. In order to avoid this problem, the dataset created by combining two different datasets, PTB-XL [38] and Chapman [39] datasets, was studied. For comparison, this study aims to classify arrhythmias through ECG recordings containing 12 lead signals by training both SE-ResNet34 and FCN deep neural networks.

There are a lot of articles in the literature about arrhythmia classification in machine learning. Some of the studies on arrhythmia classification according to chronological order can be seen in Table 3.1.

Table 3.1 Articles in the Literature About Arrhythmia Classification

Year	Article Title	Method	Summary
1991	Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection [52]	Adaptive Filtering	The adaptive filter minimizes the mean-squared error for ECG signals. It was used to detect arrhythmias such as AF and PVC.
2009	ECG Arrhythmia Classification with Support Vector Machines and Genetic Algorithm [51]	Support Vector Machines, Genetic Algorithm	Four types of arrhythmias were distinguished with 93% accuracy.
2018	Cardiac arrhythmia classification by multi-layer perceptron and convolution neural networks [42]	Multi-Layer Perceptron, Convolutional Neural Networks	As a result of the study, a success rate of 88.67% was achieved with multilayer Percetron and 83.5% with convolutional neural networks.
2019	Automatic Cardiac Arrhythmia Classification Using Combination of Deep Residual Network and Bidirectional LSTM [41]	Deep Residual Network, Bidirectional LSTM	Recordings have variable lengths from 6 to 60 seconds. As a result of the study, an F1 score value of 80.6% was obtained.
2019	Cardiologist level arrhythmia detection and classification in ambulatory	Deep Neural Networks (DNN)	The F1 score value obtained as a result of the study is 0.8337, and this value is higher than the

	electrocardiograms using a deep neural network [43]		average cardiologist score of 0.780.
2019	ECG Arrhythmia Classification Using STFT-Based Spectrogram and Convolutional Neural Network [44]	CNN-1D, CNN-2D, Fourier Transformation	5 different arrhythmia categories were studied. A success rate of 90.93% was achieved.
2022	Deep Learning Models for Arrhythmia Detection in IoT Healthcare Applications [54]	CNN, ConvLSTM	It has achieved success rates ranging from 91% to 97%.

In addition to those mentioned in Table 3.1, there are many studies in the literature on arrhythmia classification studies. In studies before the last 5 years, it is seen that machine learning techniques are used more widely instead of artificial neural networks. Since the success rate of artificial neural networks can be higher, the use of artificial neural networks in arrhythmia classification studies has increased [45].

The current thesis study has differences from the studies in the literature. The most important of these is the definition of the 'no arrhythmia' class to classify ECG recordings that do not contain any arrhythmia. If the 'no arrhythmia' class was not defined, then ECG records containing no arrhythmia could be classified using the threshold value method. However, how to determine the threshold value is an important issue here. There are studies using the threshold approach to classify multi-label arrhythmias and ECG recordings that do not contain any arrhythmia [47]. However, it is not stated here how the threshold value is determined.

Studies in the literature show success rates of up to 90%. However, these success rates are generally the success rates of a single data set. A study in the literature achieved a success rate of 68% in the training set and 31% in the foreign data set [37]. To avoid these problems, two separate data sets were combined to obtain a single data set, and all results were obtained from the combined data set. In arrhythmia classification studies based on ECG records, combining different data sets to obtain a single data set and obtaining the results from the combined data set is an important issue that distinguishes the thesis study from other studies.

4. UTILIZED DATASETS & EVALUATION METRICS

This section describes the characteristics of the studied datasets and evaluation metrics.

4.1 Datasets

In this section, the studied datasets are explained in detail. To classify arrhythmia through ECG signals, two different data sets were combined to obtain a single data set. The reason for doing this is to prevent the trained model from focusing on a single data set. In the literature, there are arrhythmia classification studies that provide a 68% success rate on the test dataset when the dataset is divided into training and test, while a 31% success rate is achieved when a foreign dataset is given as the test set [37].

A more balanced data set was obtained by combining two different data sets. Because while some arrhythmias in the PTB-XL dataset are much more common than in the Chapman dataset, some arrhythmias in the Chapman dataset are also more common in the PTB-XL dataset.

4.1.1 PTB-XL Dataset [38]

It is a popular dataset used in arrhythmia classification studies. There are 21837 ECG records taken from 18885 patients in the 7-year period between 1989 and 1996. All ECG recordings are 10-second recordings. There are 500 samples for each second. Since all recordings are 10 seconds long, each recording contains 5000 samples in total. Each ECG recording contains the entire 12-lead signal. ECG records also include patients' age and gender information.

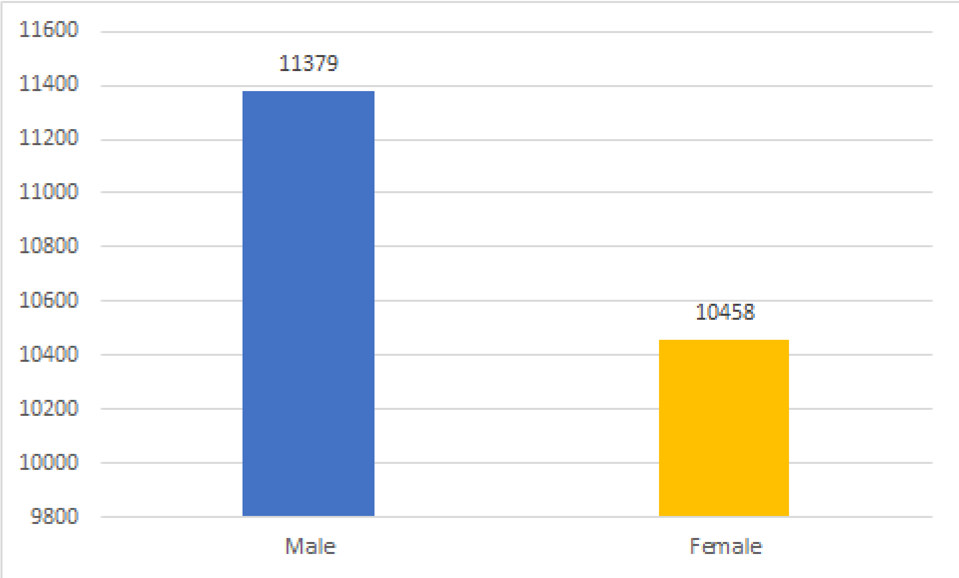

Figure 4.1 Gender Distribution on the PTB-XL Dataset

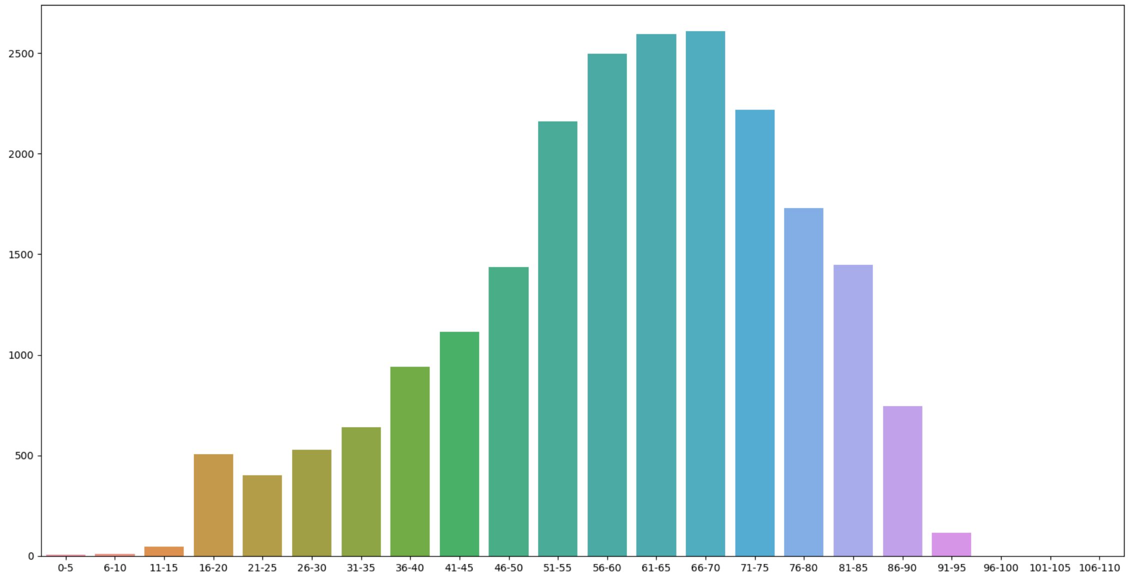

Figure 4.2 Age Distribution on the PTB-XL Dataset

Table 4.1 The 10 Most Popular Arrhythmias in the PTB-XL Dataset

Index	Arrhythmia Name	Abbreviation	Arrhythmia Count
1	Sinus Rhythm	SNR	18092
2	Myocardial Infarction	MI	5261
3	Left Axis Deviation	LAD	5146
4	Abnormal QRS	abQRS	3389
5	Left Ventricular Hypertrophy	LVH	2359
6	T Wave Abnormal	TAb	2345
7	Myocardial Ischemia	MIs	2175
8	Left Anterior Fascicular Block	LAnFB	1626
9	Atrial Fibrillation	AF	1514
10	Ventricular Ectopics	VEB	1154

4.1.2 Chapman Dataset [39]

ECG recordings served by Shaoxing Human Hospital, Chapman University in China. There are 11047 ECG records. It has the same format features as the PTB-XL dataset. Each ECG recording is 10 seconds long. Each recording contains 500 samples of data per second, so there are 5000 samples in ECG records. Each ECG recording contains 12 lead signals. Each ECG record includes patients' age and gender information.

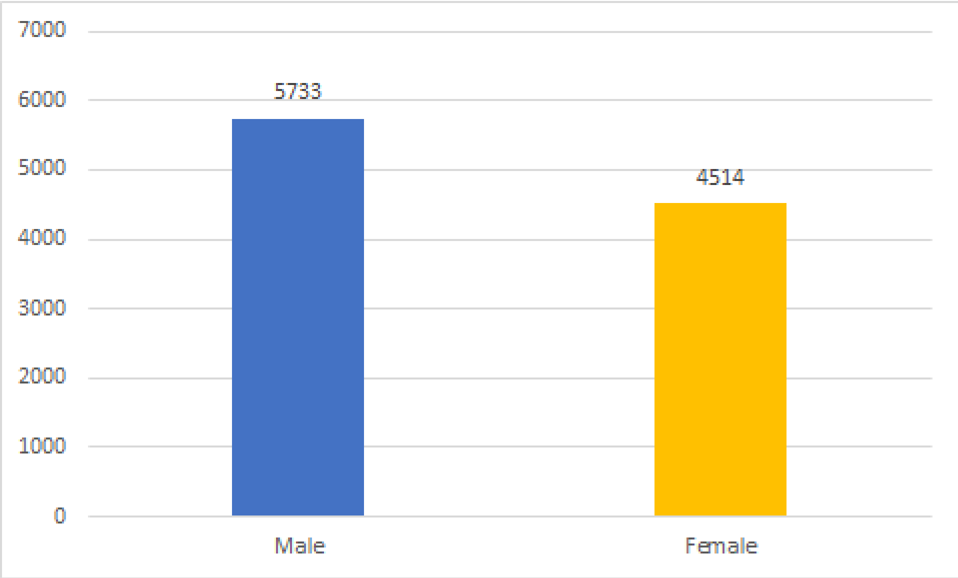

Figure 4.3 Gender Distribution on the Chapman Dataset

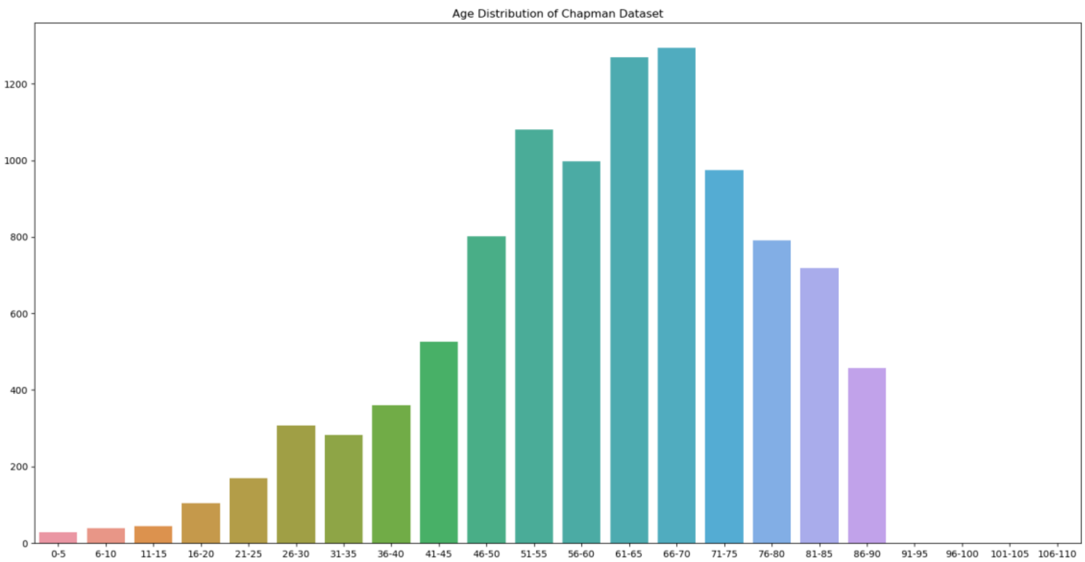

Figure 4.4 Age Distribution on the Chapman Dataset

Table 4.2 The 10 Most Popular Arrhythmias in the Chapman Dataset

Index	Arrhythmia Name	Abbreviation	Arrhythmia Count
1	Sinus Bradycardia	SB	3889
2	T Wave Abnormal	TAb	1876
3	Sinus rhythm	SNR	1826
4	Atrial Fibrillation	AF	1780
5	Sinus Tachycardia	STach	1568
6	Left Ventricular High Voltage	LVHV	1295
7	Nonspecific St T Abnormality	NSSTTA	1158
8	Supraventricular Tachycardia	SVT	1587
9	Right Bundle Branch Block	RBBB	454
10	Atrial Flutter	AFL	445

4.1.3 Overall Dataset

Both PTB-XL and Chapman datasets were combined to obtain a single dataset. All of the studies were done on this combined data set. There are a total of 32084 ECG records in the dataset.

Figure 4.5 shows that out of a total of 32084 ECG records, 17112 are male and 14972 are female. Men are 14.29% more than women.

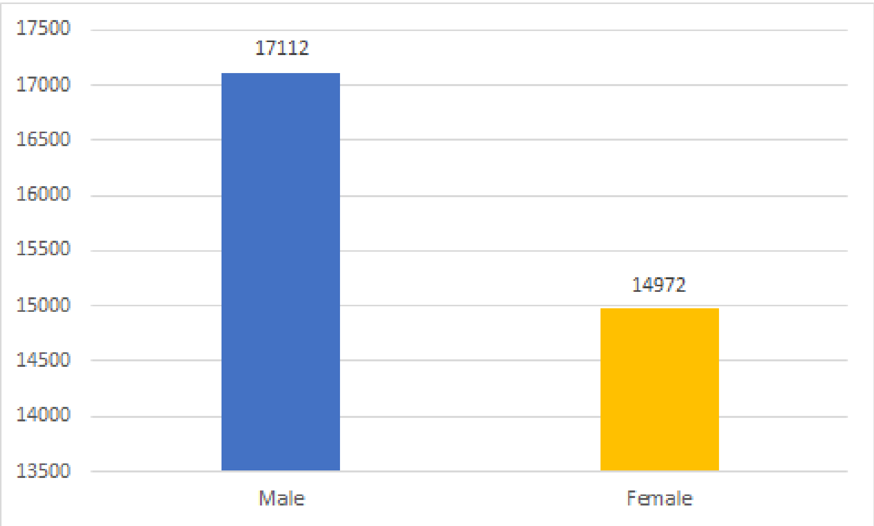

Figure 4.5 Gender Distribution on the Overall Dataset

The age distribution of 32084 ECG records starts from 2 to 95. The majority are between the ages of 61 and 70. The ECG records in this section correspond to 24.21% of the dataset. The age distribution of the patients in the 32084 ECG recordings can be seen in Figure 4.6.

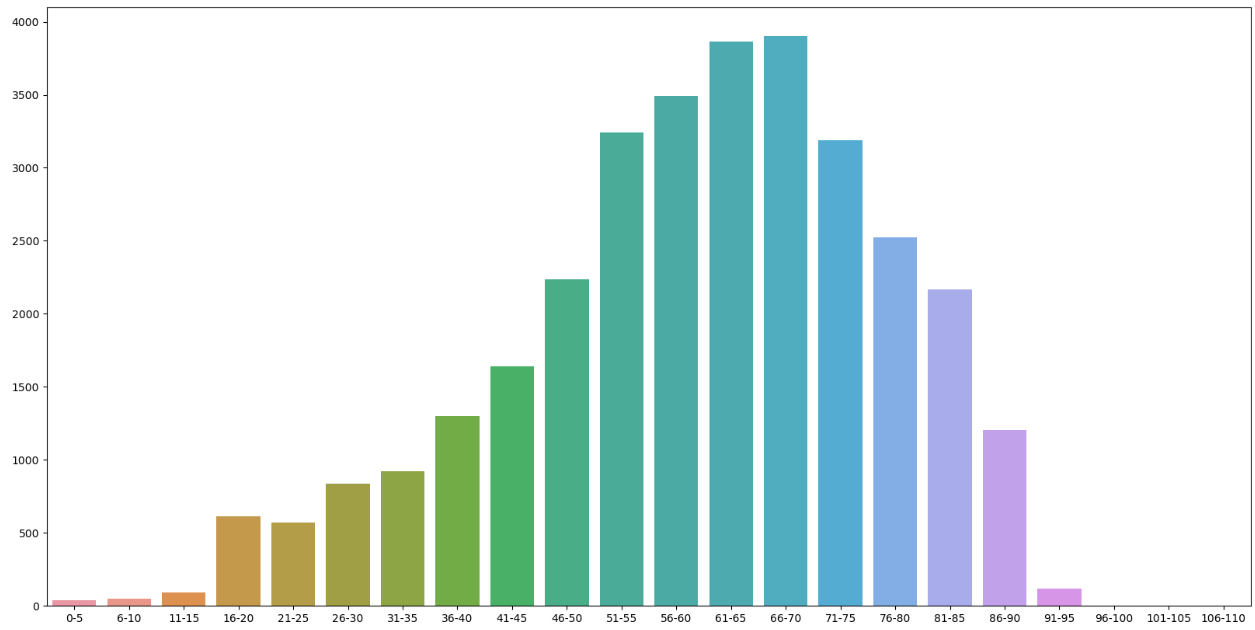

Figure 4.6 Age Distribution on the Overall Dataset

The distribution of arrhythmias in the PTB-XL and Chapman datasets separately and the distribution of arrhythmias when these datasets are combined can be seen in Table 4.3. Table 4.3 is sorted by the occurrence of arrhythmias in the combined data set.

Table 4.3 The 10 Most Popular Arrhythmias in the Overall Dataset

Index	**Dx**	**Abbreviation**	**PTB-XL**	**Chapman**	**Total**
1	Sinus rhythm	SNR	18092	1826	19918
2	Left Axis Deviation	LAD	5146	382	5528
3	Myocardial Infarction	MI	5261	40	5301
4	Sinus Bradycardia	SB	637	3889	4526
5	T Wave Abnormal	Tab	2345	1876	4221
6	Abnormal QRs	abQRS	3389	0	3389
7	Atrial Fibrillation	AF	1514	1780	3294
8	Sinus Tachycardia	STach	826	1568	2394
9	Left Ventricular Hypertrophy	LVH	2359	15	2374
10	Myocardial Ischemia	MIs	2175	0	2175

It can be seen in Table 4.3 that the frequency of occurrence of "Sinus rhythm" in the PTB-XL dataset is almost 10 times that of Chapman. However, the incidence of "Sinus bradycardia" in the Chapman dataset is more than 6 times higher than PTB-XL. As can be seen, if the study was carried out on only a single data set, there would be a majority for certain types of arrhythmia. Since two different data sets were studied, the distribution of arrhythmias became more balanced.

4.2. Evaluation Metrics

Various evaluation criteria are used to measure the success of the studies carried out in this thesis. These are F1 score, recall, accuracy and precision. These metrics can be seen in Eq. (1), (2), (3) and (4).

$$F1Score = 2 \times \frac{Recall * Precision}{Recall + Precision} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TF + FP} \tag{3}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{4}$$

These evaluation criteria are popular evaluation criteria used in the literature [46]. However, different metrics were also used to calculate the success rates of the created models in the test dataset.

5. PROPOSED METHOD

In the studies, classification studies were carried out on the 5, 10 and 15 most popular arrhythmias in the data set. In addition to these arrhythmias, the ’no arrhythmia’ class has also been defined. If an ECG recording contains no arrhythmia then the ’no arrhythmia’ class is set to 1 in one-hot-encoding. Thanks to this approach, there is no ECG record with all lines 0 in one-hot-encoding. From our studies, we achieved a higher success rate as a result of considering the ’no arrhythmia’ class as an arrhythmia class. It is very difficult to evaluate ECG recordings that do not contain any arrhythmia unless the ’no arrhythmia’ class is defined. If the ’no arrhythmia’ class was not defined, the threshold value could be used to classify ECG recordings that did not contain any arrhythmia. There are studies on this subject in the literature [47]. However, how to determine the threshold value is an important issue here. In this sense, it is a new approach to categorize the situation in which the ECG recording does not contain any arrhythmia as the ’no arrhythmia’ class.

Many different models were trained to make comparisons. These trained models can be categorized as follows:

- Multi-label training, single-label output, no threshold method
- Multi-label training, multi-label output, threshold method available

In the studies, first the number of arrhythmias to be studied is determined. After determining the number and types of arrhythmias to be studied, a one-hot-encoding sequence of each ECG record in the dataset is obtained. The approach to obtaining a one hot encoding sequence is as follows: if an ECG record contains an arrhythmia but it is not one of the arrhythmias studied, its counterpart in one-hot-encoding is that all columns are zero. For example, an ECG record may contain 3 different arrhythmias, but if none of them is the arrhythmia to be studied, then the equivalent of one hot encoding of this ECG record is that all columns are zero. In this case, that ECG recording is evaluated as ’no arrhythmia’ because it does not contain any of the arrhythmias we want to study. What this approach gives us is that no ECG records are deleted from the dataset. If we deleted the ECG records containing the arrhythmias we wanted to study from the data set, then we would be working with much fewer ECG records. Thanks to this approach, when working with 5, 10 and 15 arrhythmias, the number of ECG records in the data set is constant and equal to 32084. Of course, the number of ‘no arrhythmia’ when working with 5 arrhythmias is much higher than the number of ‘no arrhythmia’ when working with 15 arrhythmias. When working with 5 arrhythmias, there are 4559 number of ‘no arrhythmia’ classes in the data set, when working with 10 arrhythmias, there are 1452 number of ‘no arrhythmia’ classes in the data set, and when working with 15 arrhythmias, there are 1230 number of ‘no arrhythmia’ classes.

In the multi-label training and single-label output approach, the probability values of arrhythmias are examined. The arrhythmia class with the highest prediction score is the output of the model. If the arrhythmia class found as a result of the model is mentioned in the ECG record, the prediction process is considered successful, if not, the prediction process is considered unsuccessful. For example, an ECG recording with arrhythmia types A and B is considered successful whether the model produces arrhythmia A or arrhythmia B as output. This approach is quite optimistic; however, ECG recording can be evaluated with very high success rates. This approach is quite good if the ECG recording contains no or a single arrhythmia. However, if an ECG recording contains more than one arrhythmia, only a single one can be detected.

When we look at the studies on ECG recordings, there are not many studies on multi-label training and multi-label output [48]. The most important issue here is how the model will produce multi-label output. It is seen that the threshold method is used in articles published on this subject [47]. However, this article does not explain how the threshold value is determined.

The multi-label training multi-label output approach is actually an advanced version of the multi-label training single-label output approach. Here the model can produce multiple outputs. To produce multiple arrhythmia results, the predictive values of all arrhythmias are checked one by one. If the predicted value of any arrhythmia is higher than the threshold value, then that arrhythmia becomes the output of the model. If there is no arrhythmia exceeding the threshold value, then the arrhythmia with the highest probability value is considered as the output of the model. Many studies have been conducted to determine the ideal threshold value. In the Experimental Results section, the success of models with different threshold values will be explained comparatively. In the FCN model, the ideal threshold value for all scenarios is fixed and this value is 0.55. In the ResNet model, there are differences in the ideal threshold value. The ideal threshold value is 0.35 when working with 5 arrhythmias, and 0.10 when working with 10 and 15 arrhythmias. The approach here is that each arrhythmia has a fixed threshold value and when that threshold value is exceeded, the relevant arrhythmia is the output of the model.

In addition to the fixed threshold approach, threshold values can be determined separately for each arrhythmia. For this, the outputs produced by the model on the validation set and the arrhythmias in the validation set are examined. In the ECG records where each arrhythmia is active in the validation set, it is checked what predictive values the model produces for that arrhythmia. A threshold value is determined based on these values. In this approach, a higher success rate can be achieved than the fixed threshold value method, since the threshold value is calculated separately for each type of arrhythmia. However, the approach to determining threshold values should be done separately for each model. Because when working with 5 arrhythmias, the ideal threshold value for sinus arrhythmia is 0.45, while when working with 10 arrhythmias, the ideal threshold value for sinus arrhythmia may be 0.50. Therefore, although this approach may yield higher success rates, it is not generalizable.

K-Fold Cross Validation method was used in each model study and the k value was taken as 10. When training the model, only the first fold was used for training purposes. In addition to this, shuffle method was used to obtain balanced dataset.

We implemented all the models with Spyder 3.5 and trained them on machines with AMD Radeon Graphics 512 MB. A learning rate of 0.001 was used. The adaptive momentum estimation (Adam) optimizer was used to optimize the network parameters.

5.1. ResNet Model

A 34-layer Residual Network model was designed to classify arrhythmias through ECG recordings. 17 sequential skip connections are available to increase the success of the one-dimensional CNN (1D Conv) network [49]. Transactions made in each block repeat each other. As can be seen from Figure 5.1, the module includes a Batch normalization layer, one-dimensional convolutional layer, ReLU activation layer and SE layer.

In convolutional neural networks, the convolution layer is the basic learning component of convolutional neural networks. Here is a 7x1 filter with learnable weights. When important features are detected, the filter is activated by adjusting the weights. By providing labeled data, the model can learn important features for different classes of arrhythmias.

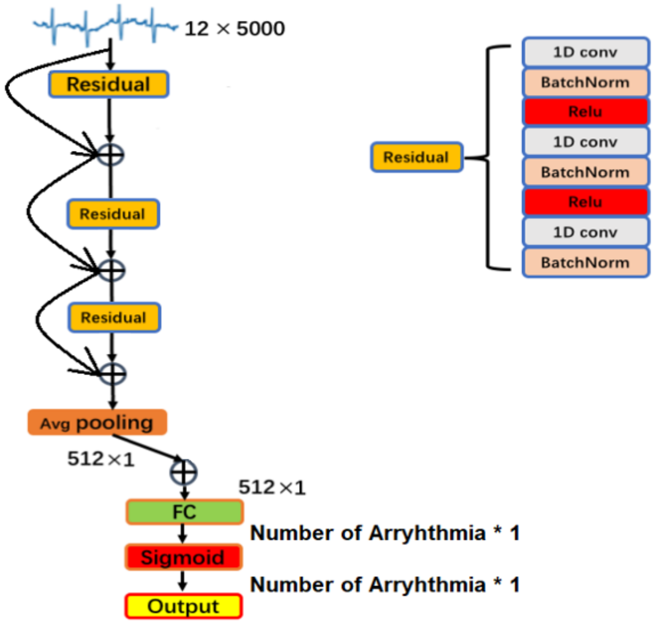

Figure 5.1 The Overall Structure of Residual Network Model

Because each learned filter worked with a local receptive field, each unit of the transformation output could not benefit from contextual information outside this field. It is aimed to solve the problem of exploiting channel dependencies with the SE layer (Squeeze and Excitation block) [50].

First, we compressed global spatial information into a channel descriptor using global average pooling. In formulaic terms, minimizing $\mathcal{U}$ along the $H \times W$ spatial dimensions produced a $z \in \mathbb{R}^c$ statistic; where the c-th element of z is calculated as follows:

$$z_c = F_{sq}(u_c) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} u_c(i,j) \tag{1}$$

Here $\mathcal{U} = [u_1, u_2, \ldots, u_3]$ was the output of previous layer, $\mathcal{U} \in \mathbb{R}^{H \times W \times C}$. The transformation output $\mathcal{U}$ could be interpreted as a collection of the local descriptors, which were expressive for the whole signal.

Secondly, to make use of the information aggregated in the squeeze operation and fully capture channel-wise dependencies, a simple gating mechanism with a sigmoid function was used. The Eq. (2) was used to learn the non-mutually exclusive relationship of this simple transition mechanism:

$$s = F_{ex}(z, W) = \sigma\big(g(z, W)\big) = \sigma\big(W_2 \delta(W_1 z)\big) \tag{2}$$

Where δ refers to the ReLU function, $W_1 \in \mathbb{R}^{\frac{C}{r} \times C}$ and $W_2 \in \mathbb{R}^{\frac{C}{r} \times C}$, r = 16. To reduce the complexity that may occur in the model and improve generalization, a simple gate mechanism was parameterized by creating a bottleneck with two fully connected layers. To perform this process, the dimension reduction layer was used with r reduction ratio and W_1 parameter. ReLU activation function and dimensionality increase layer were used with W_2 parameter. The final output of the block was obtained by rescaling the transformation output $\mathcal{U}$ with the activation function:

$$\tilde{X}_c = F_{scale}(u_c, s_c) = s_c \cdot u_c \tag{3}$$

Where $\tilde{X} = [\tilde{x}_1, \tilde{x}_2, \dots, \tilde{x}_3]$ and $F_{scale}(u_c, s_c)$ refers to channel-wise multiplication between the feature map $u_c \in \mathbb{R}^{H \times W}$ and the scalar s_c.

Following this, a fully connected layer was used to transform the features to a [Number Of Studied Arrhythmia × 1] vector of numerical values, which corresponded to the outputs for each class. The sigmoid function was used to display these values as probabilities and produce results between 0 and 1. The network structure takes 10-second ECG recordings as input and produces a prediction for each arrhythmia. The closer to zero the value obtained from the sigmoid function as a result of the prediction made in the ECG recording, the less likely it is that the relevant arrhythmia will be found in the ECG recording. Similarly, the closer to one the output of the sigmoid function is, the more likely it is that the relevant arrhythmia will be present in the ECG recording.

5.2. FCN Model

The developed Fully Convolutional Network structure is quite simple compared to ResNet. Again, since the total number of samples of each ECG record is 5000 and there are a total of 12 lead signals, an input of size (5000, 12) is taken. A 3-layer Conv 1D network structure is used in the hidden layer. The activation function in each of these layers is ReLU. There are as many neurons as the number of arrhythmias studied in the output layer and the activation function is sigmoid. The FCN model structure can be seen in Figure 5.2.

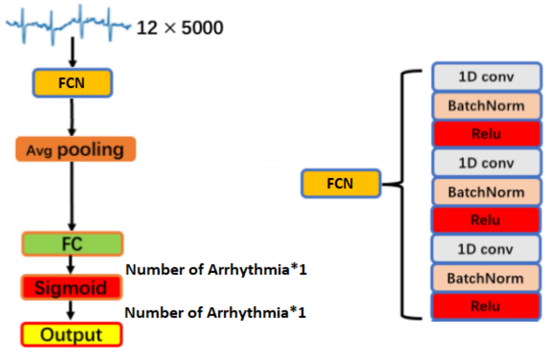

Figure 5.2 The Overall Structure of Fully Convolutional Network

5.3. Weight Function

Some types of arrhythmia may be more common than other types of arrhythmia in the dataset. This may prevent the model from focusing on more common arrhythmias in the data set and thus successfully detecting less common arrhythmia types. To avoid this problem, a weight function was designed to be used in model training. Thus, less weight was given to the more common arrhythmia types in the data set, and higher weight was given to the less common ones. The relevant equation can be seen in the following:

$$weight[i] = \sqrt{\frac{Number\ of\ ECG}{4 * bincount(y\_arr[i])}} \tag{4}$$

Number Of ECG refers to the total number of ECG recordings in the dataset. bincount is a function here. Counts the number of times the relevant arrhythmia appears and does not appear in the data set. y_arr refers to the column of the arrhythmia in one-hot-encoding. Square rooting was used for smoothing. Thanks to this function, less weight is given to common arrhythmia types in the data set, while more weight is given to less common arrhythmia types.

A good weight function can increase model success. In addition, it is very important to use the weight function in arrhythmia classification studies. Because while some arrhythmias are quite common in the data set, some arrhythmias are very rare. This makes it difficult to classify the small number of arrhythmias in the data set. To prevent this, the weight function should be used.

6. EXPERIMENTAL RESULTS

6.1 Multi Label Training – Single Label Output

The success and other features of the ResNet & FCN models in the data set consisting of ECG recordings in the multi-label training single-label output approach are shown in Table 6.1.

Table 6.1 Multi Label Training-Single Label Output ResNet, FCN Model Results

Model Type	ResNet	FCN	ResNet	FCN	ResNet	FCN
Number of Arrhythmias Studied	5	5	10	10	15	15
No Arrhythmia Class is Available	Yes	Yes	Yes	Yes	Yes	Yes
Total Number of Classes Studied	6	6	11	11	16	16
Number of ECG Recordings Containing No Arrhythmia	4559	4559	1452	1452	1230	1230
Number of ECG Recordings Containing 1 Arrhythmia	17872	17872	16789	16789	14868	14868
Number of ECG Recordings Containing 2 Arrhythmia	7383	7383	7931	7931	7972	7972
Number of ECG Recordings Containing 3 Arrhythmia	2224	2224	3677	3677	4349	4349
Number of ECG Recordings Containing 4 Arrhythmia	46	46	1812	1812	2374	2374
Number of ECG Recordings Containing 5 Arrhythmia	0	0	348	348	1012	1012
Number of ECG Recordings Containing 6 Arrhythmia	0	0	75	75	226	226

Number of ECG Recordings Containing 7 Arrhythmia	0	0	0	0	50	50
Number of ECG Recordings Containing 8 Arrhythmia	0	0	0	0	3	3
Number of Total ECG	32084	32084	32084	32084	32084	32084
Total Number of Unique Combinations	27	27	238	238	813	813
Accuracy Score	0,837	0,878	0,804	0,899	0,835	0,90

As can be seen in Table 6.1, the unique combination numbers of arrhythmias in the dataset are also shown in each model run. It appears that as the number of arrhythmias studied increases, the number of unique combinations also increases. When training the data set, care should be taken to treat ECG recordings that do not contain any arrhythmia as containing the 'no arrhythmia' class. For example, if 5 different arrhythmias are studied, there should be 6 cells in the output layer. Because if the 'no arrhythmia' class is included, there are 6 different classes. An ECG recording may contain any or none of 5 different arrhythmias. This allows us to classify ECG recordings that do not contain any arrhythmia.

As can be noticed in Table 6.1, the number of ECG recordings studied is always constant. In Table 6.1, it is important to pay attention the number of ECG recordings that do not contain any arrhythmia. As the number of arrhythmias studied increases, the number of ECG recordings containing no arrhythmia decreases. The reason for this is that when working with 5 arrhythmias, the types of arrhythmias in the ECG records in the data set may not be one of these 5 arrhythmias. ECG records that do not contain any of these 5 arrhythmias are also considered as ’no arrhythmia’. When working with 15 arrhythmias, many ECG records in the data set are covered. Because it covers many ECG records from the 15 most popular arrhythmia datasets. Since there are a small amount of ECG records not covered, the number of ‘no arrhythmia’ ECG records when working with 15 arrhythmias is less than the number of ‘no arrhythmia’ ECG records when working with 5 arrhythmias.

The same studies done for ResNet in Table 6.1 were also done for the Fully Connected Layer network structure. While the results of ResNet and FCN are obtained, the only difference is the network structures. No change in the weight function or pre-processing operation was made.

As can be seen from the comparison of Table 6.1, the success of the FCN model is greater than the ResNet model when all other conditions remain the same.

6.2 Multi Label Training – Multi Label Output

Multi-label training multi-label output approach is an improved version of multi-label training single-label output. The difference here is that the arrhythmia with the highest predictive value is not considered as the output of the model. Each arrhythmia is compared individually with the determined threshold value. All arrhythmias exceeding the threshold value are the output of the model. If any arrhythmia does not exceed the threshold value, then the arrhythmia with the highest probability value becomes the output of the model.

The success rates obtained when 0.40, 0.45, 0.50, 0.55, 0.60 and 0.65 are given as threshold values for FCN model, respectively, can be seen in Table 6.2.

Table 6.2 Threshold Value Effect When Working With 5, 10, 15 Arrhythmias in the FCN Model

Number of Arrhythmias Studied	No Arrhythmia Class is Available	Total Number of Classes Studied	Threshold	Accuracy Score
5	Yes	6	0,40	0,626
5	Yes	6	0,45	0,639
5	Yes	6	0,50	0,650
5	**Yes**	**6**	**0,55**	**0,660**
5	Yes	6	0,60	0,658
5	Yes	6	0,65	0,653
10	Yes	11	0,40	0,540
10	Yes	11	0,45	0,552
10	Yes	11	0,50	0,552
10	**Yes**	**11**	**0,55**	**0,553**
10	Yes	11	0,60	0,550
10	Yes	11	0,65	0,541
15	Yes	16	0,40	0,492
15	Yes	16	0,45	0,502
15	Yes	16	0,50	0,506
15	**Yes**	**16**	**0,55**	**0,507**
15	Yes	16	0,60	0,501

15	Yes	16	0,65	0,490

The only difference in obtaining Table 6.2 is the threshold values. Other than that, the models are exactly the same. Generally, the highest success rate was achieved at a threshold value of 0.55 in all cases. In line with the results obtained from the table here, it can be stated that the ideal threshold value is 0.55 for the FCN model. When Table 6.2 is examined, it is seen that success rates decrease as we move away from the ideal threshold value, and success rates increase as we approach the ideal threshold value.
When the threshold value is selected as 0.55, the multi-label training multi-label output results of the FCN model on 5, 10 and 15 arrhythmias can be seen in the Figures and Tables below.
In multi-label training, multi-label output study, the standard confusion matrix cannot be used because there may be more than one arrhythmia in an ECG recording. As explained Section 2.10, the confusion matrix is calculated separately for each class.

Table 6.3 FCN Model, Classification Report, 5 Arrhythmia, Threshold=0,55

	precision	recall	f1-score	support
MI	0,775	0,623	0,691	531
TAb	0,556	0,306	0,394	422
LAD	0,740	0,593	0,659	553
SB	0,902	0,914	0,908	452
SNR	0,931	0,954	0,943	1992
NO_ARR	0,724	0,759	0,741	456

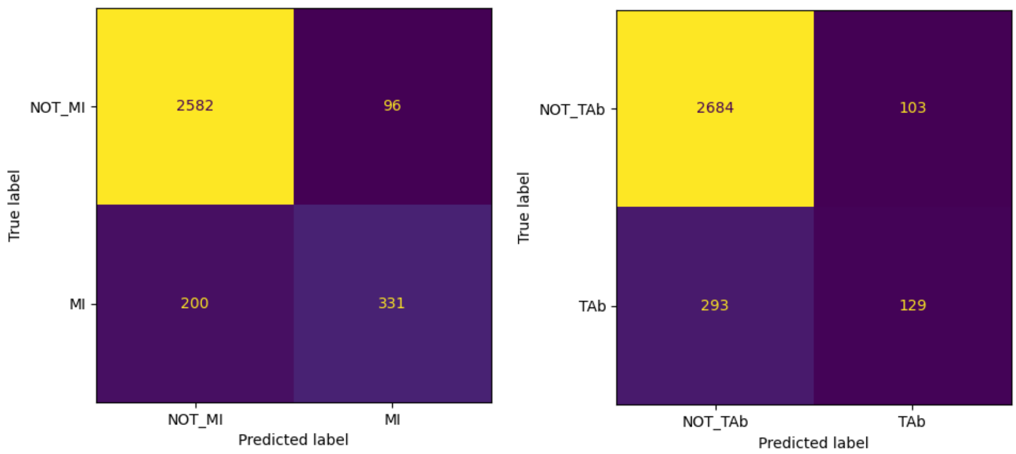

Figure 6.1 Confusion Matrix, FCN Model, 5 Arrhythmia, Arrhythmia Type: MI, TAb Threshold=0,55

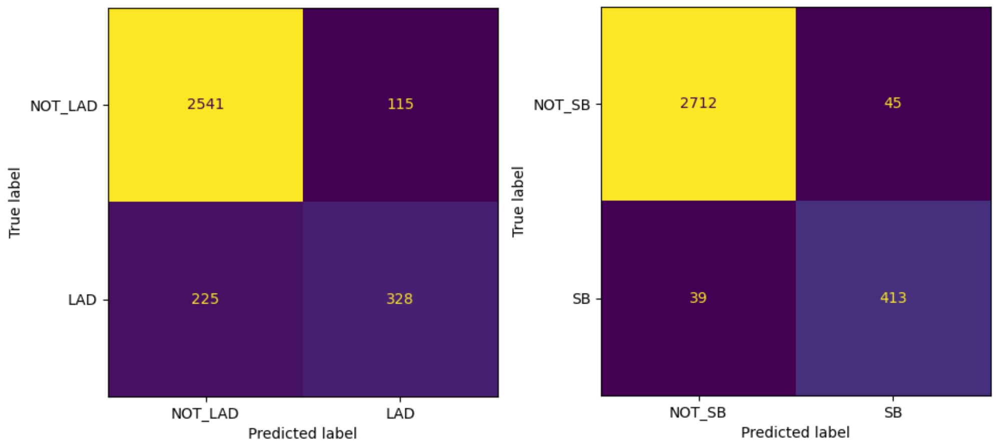

Figure 6.2 Confusion Matrix, FCN Model, 5 Arrhythmia, Arrhythmia Type: LAD, SB Threshold=0,55

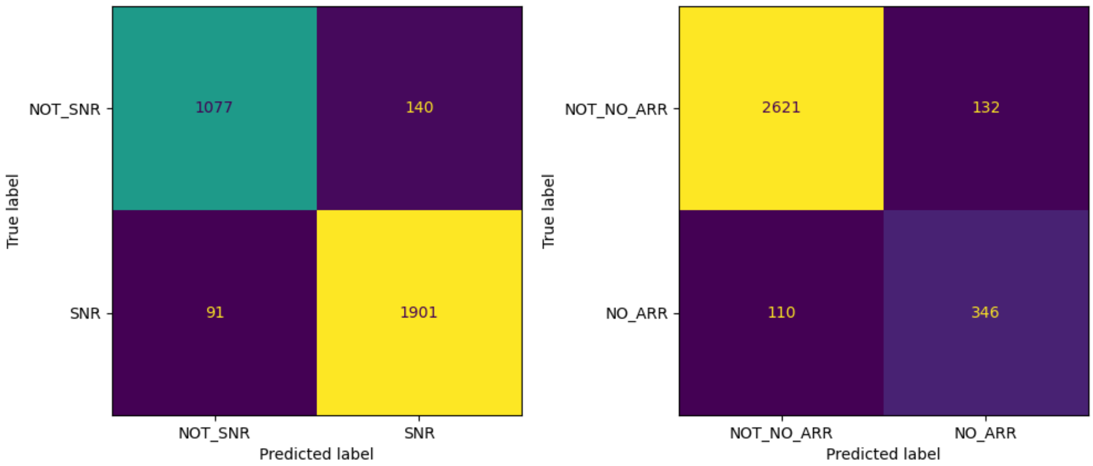

Figure 6.3 Confusion Matrix, FCN Model, 5 Arrhythmia, Arrhythmia Type: SNR, NO_ARR Threshold=0,55

Table 6.4 FCN Model, Classification Report, 10 Arrhythmia, Threshold=0,55

	precision	recall	f1-score	support
MIs	0,715	0,544	0,618	217
MI	0,770	0,513	0,616	528
LVH	0,727	0,400	0,516	240
AF	0,858	0,864	0,861	323
TAb	0,620	0,232	0,337	423
abQRS	0,796	0,319	0,455	342
LAD	0,734	0,473	0,575	548
SB	0,906	0,850	0,877	454
SNR	0,925	0,936	0,930	1995

STach	0,824	0,855	0,839	235
NO_ARR	0,742	0,655	0,696	145

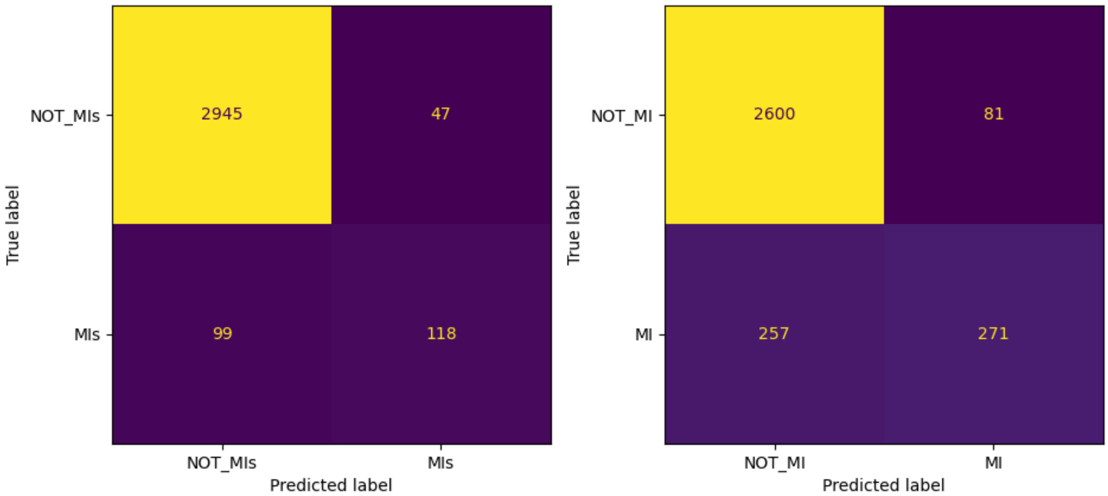

Figure 6.4 Confusion Matrix, FCN Model, 10 Arrhythmia, Arrhythmia Type: MIs, MI Threshold=0,55

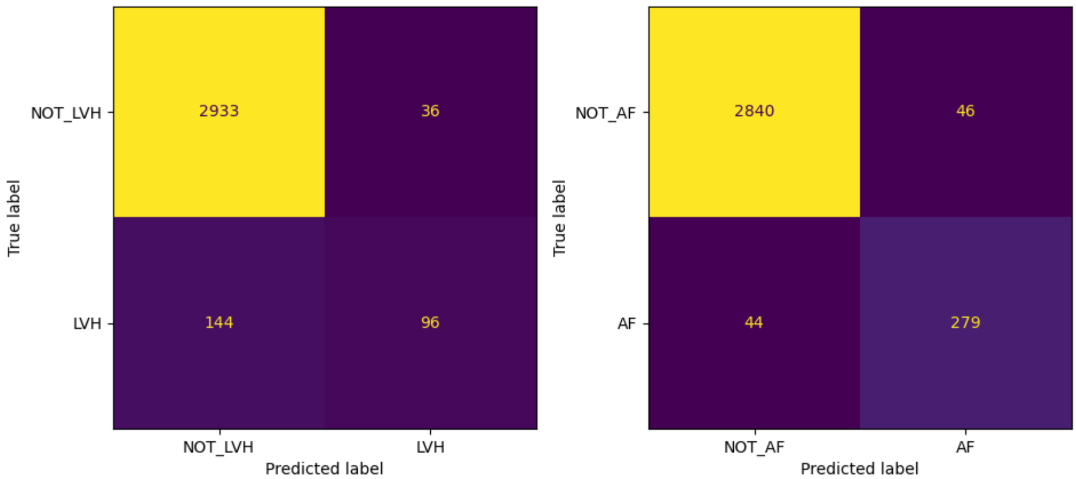

Figure 6.5 Confusion Matrix, FCN Model, 10 Arrhythmia, Arrhythmia Type: LVH, AF Threshold=0,55

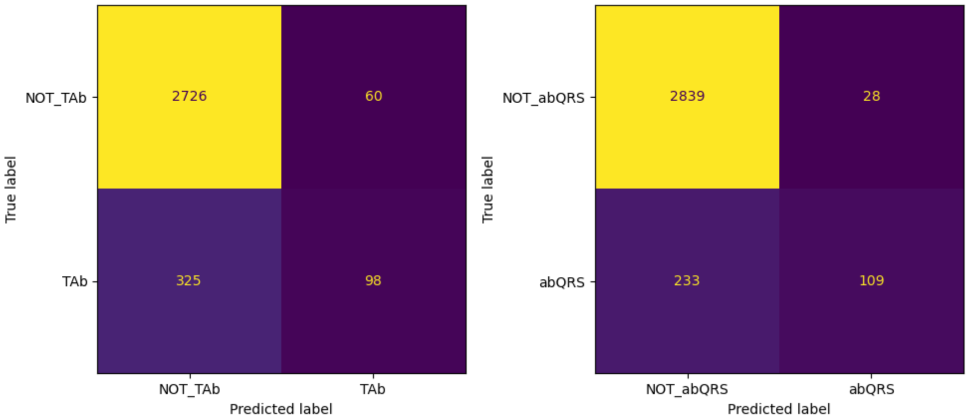

Figure 6.6 Confusion Matrix, FCN Model, 10 Arrhythmia, Arrhythmia Type: TAb, abQRS Threshold=0,55

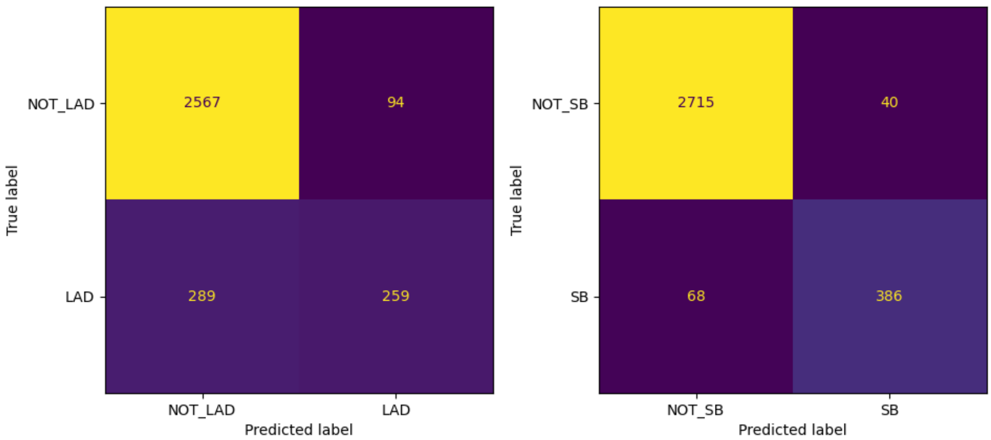

Figure 6.7 Confusion Matrix, FCN Model, 10 Arrhythmia, Arrhythmia Type: LAD, SB Threshold=0,55

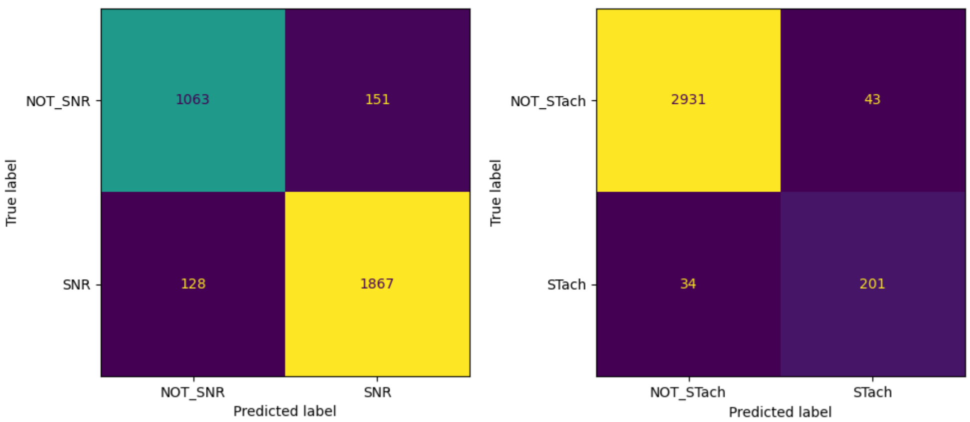

Figure 6.8 Confusion Matrix, FCN Model, 10 Arrhythmia, Arrhythmia Type: SNR, STach Threshold=0,55

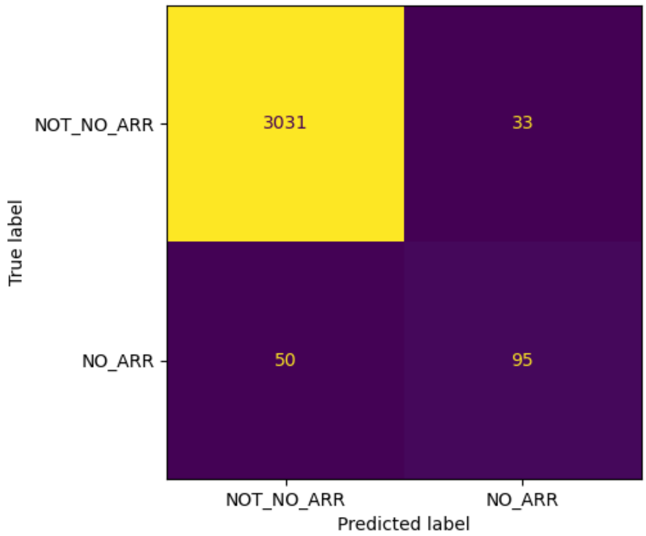

Figure 6.9 Confusion Matrix, FCN Model, 10 Arrhythmia, Arrhythmia Type: NO_ARR, Threshold=0,55

Table 6.5 FCN Model, Classification Report, 15 Arrhythmia, Threshold=0,55

	precision	recall	f1-score	support
MIs	0,766	0,566	0,651	226
MI	0,815	0,542	0,651	528
LVH	0,711	0,432	0,537	250
VEB	0,571	0,209	0,306	115
AF	0,872	0,891	0,881	329
TAb	0,600	0,253	0,356	415
abQRS	0,711	0,373	0,489	343
LAD	0,721	0,576	0,640	549
SB	0,892	0,904	0,898	448
SNR	0,937	0,928	0,932	1991
STach	0,832	0,843	0,837	235
NSSTTA	0,630	0,192	0,294	151
STD	0,250	0,023	0,042	132
LAnFB	0,757	0,561	0,644	155
LVHV	0,638	0,285	0,394	130
NO_ARR	0,684	0,650	0,667	123

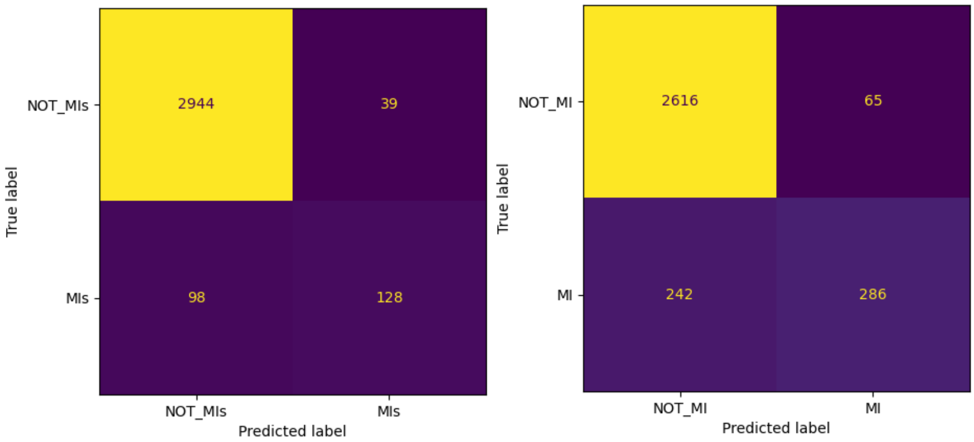

Figure 6.10 Confusion Matrix, FCN Model, 15 Arrhythmia, Arrhythmia Type: MIs, MI Threshold=0,55

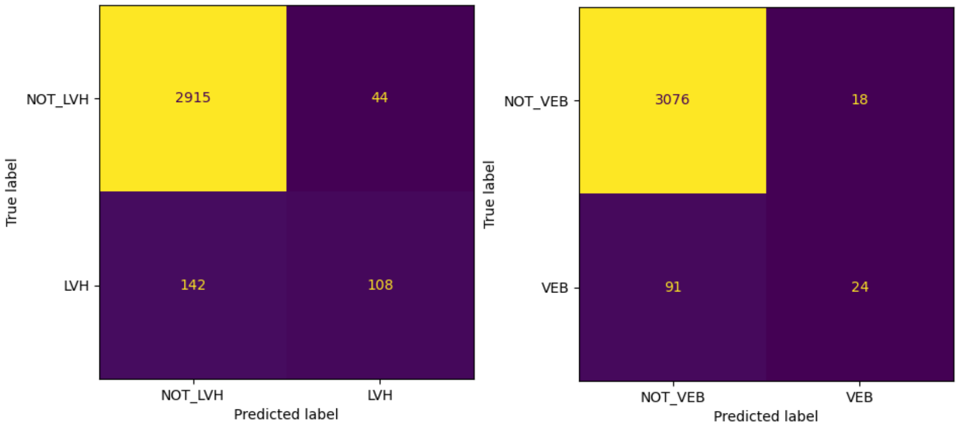

Figure 6.11 Confusion Matrix, FCN Model, 15 Arrhythmia, Arrhythmia Type: LVH, VEB Threshold=0,55

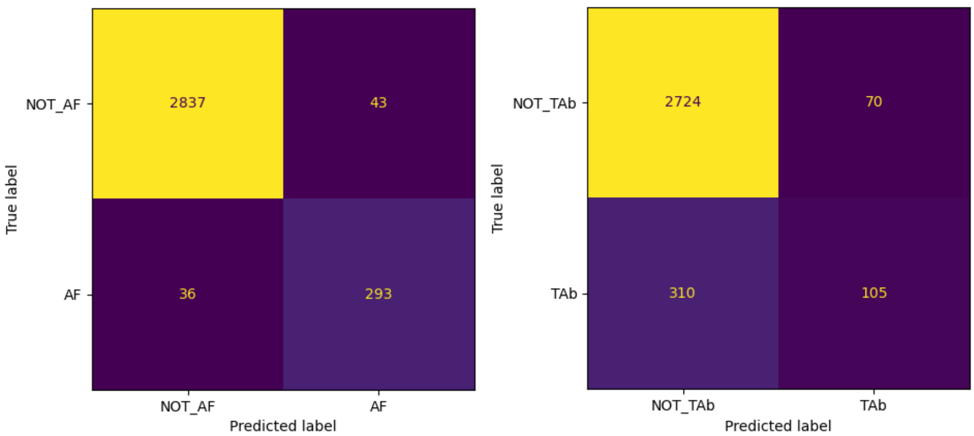

Figure 6.12 Confusion Matrix, FCN Model, 15 Arrhythmia, Arrhythmia Type: AF, Tab Threshold=0,55

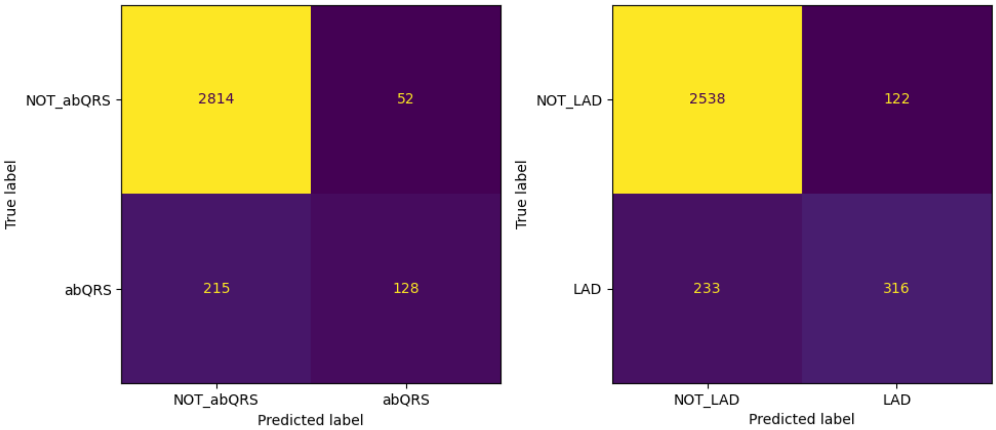

Figure 6.13 Confusion Matrix, FCN Model, 15 Arrhythmia, Arrhythmia Type: abQRS, LAD Threshold=0,55

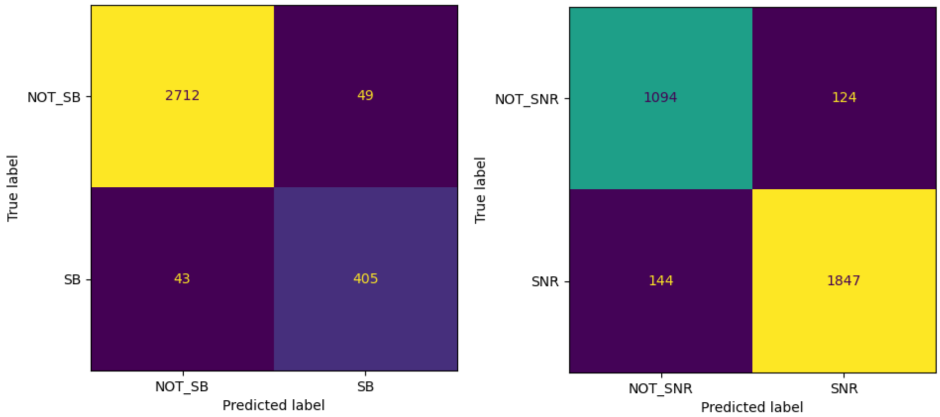

Figure 6.14 Confusion Matrix, FCN Model, 15 Arrhythmia, Arrhythmia Type: SB, SNR Threshold=0,55

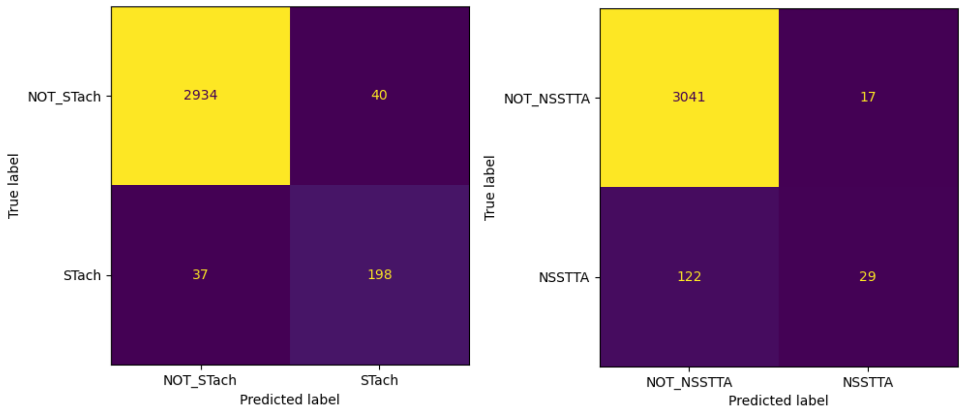

Figure 6.15 Confusion Matrix, FCN Model, 15 Arrhythmia, Arrhythmia Type: STach, NSSTA Threshold=0,55

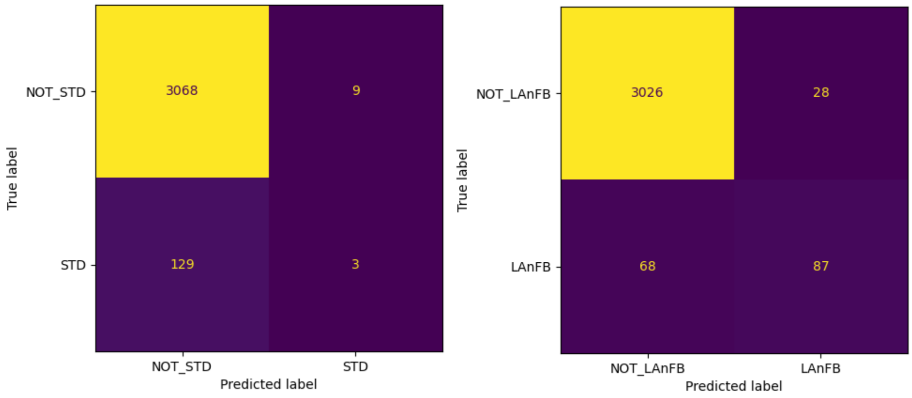

Figure 6.16 Confusion Matrix, FCN Model, 15 Arrhythmia, Arrhythmia Type: STD, LanFB Threshold=0,55

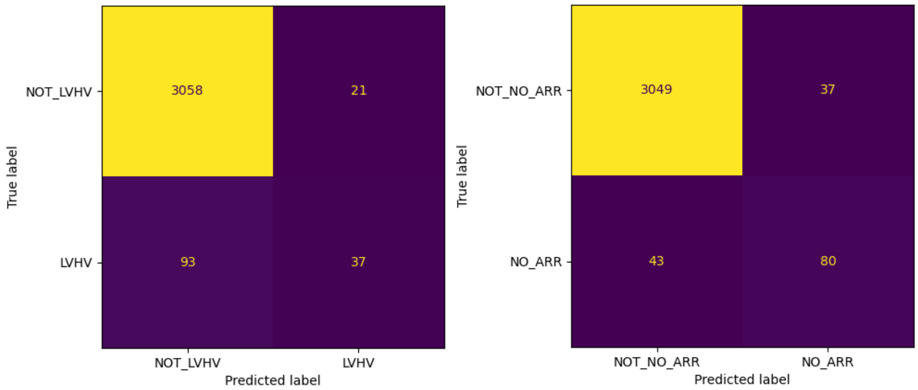

Figure 6.17 Confusion Matrix, FCN Model, 15 Arrhythmia, Arrhythmia Type: LVHV, NO_ARR Threshold=0,55

The same multi-label training and multi-label output studies conducted for FCN were also performed for ResNet. The success rates obtained when 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35 and 0.40 are given as threshold values for ResNet model, respectively, can be seen in Table 6.6.

Table 6.6 Threshold Value Effect When Working With 5, 10, 15 Arrhythmias in the ResNet Model

Number of Arrhythmias Studied	No Arrhythmia Class is Available	Total Number of Classes Studied	Threshold	Accuracy Score
5	Yes	6	0,05	0,583
5	Yes	6	0,10	0,608
5	Yes	6	0,15	0,614
5	Yes	6	0,20	0,615
5	Yes	6	0,25	0,615
5	Yes	6	0,30	0,615

5	**Yes**	**6**	**0,35**	**0,618**
5	Yes	6	0,40	0,617
10	Yes	11	0,05	0,533
10	**Yes**	**11**	**0,10**	**0,545**
10	Yes	11	0,15	0,541
10	Yes	11	0,20	0,539
10	Yes	11	0,25	0,536
10	Yes	11	0,30	0,531
10	Yes	11	0,35	0,528
10	Yes	11	0,40	0,527
15	Yes	16	0,05	0,48
15	**Yes**	**16**	**0,10**	**0,482**
15	Yes	16	0,15	0,479
15	Yes	16	0,20	0,473
15	Yes	16	0,25	0,471
15	Yes	16	0,30	0,468
15	Yes	16	0,35	0,465
15	Yes	16	0,40	0,461

In Table 6.6, the highest threshold value is shown as 0,40. Because, there was no change in the success rate at threshold values from 0,40 to 0,95.

The reason why the success rate does not change between the threshold values of 0,40 and 0,95 is due to the sharpness of the model prediction scores. As a result of the model, the prediction score of an arrhythmia belonging to an ECG record may be 0,95. The prediction score of other arrhythmias may vary between 0,01 – 0,05. In this case, no change in success rates can be seen when the threshold value changes between 0,40 and 0,95.

There is another reason why success rates change despite the increase in the threshold value. The prediction scores produced by the ResNet model for ECG recordings are not always sharp. Sometimes the prediction scores of arrhythmias from an ECG recording do not exceed 0,40. In this case, when the threshold value is between 0,40 – 0,95, no arrhythmia can exceed the threshold value. When any arrhythmia does not exceed the threshold value, the arrhythmia with the highest predictive value becomes the output of the model. Thus, whether the threshold value is 0,40 or 0,95, the same result is produced and the success rate does not change.

The only difference in obtaining Table 6.6 is the threshold values. Other than that, the models are exactly the same.

While working on 10 and 15 arrhythmias with the ResNet model, the highest success rate was obtained when the threshold value was 0,10. The highest success rate when working with 5 arrhythmias was achieved when the threshold value was 0,35. These threshold values were used in the classification report and confusion matrix studies of the ResNet model. Multi-label training multi-label output results of the ResNet model on 5, 10 and 15 arrhythmias can be seen in the Figures and Tables below.

Table 6.7 ResNet Model, Classification Report, 5 Arrhythmia, Threshold=0,35

	precision	recall	f1-score	support
MI	0,844	0,448	0,588	531
TAb	0,600	0,235	0,337	422
LAD	0,836	0,241	0,374	553
SB	0,972	0,907	0,938	452
SNR	0,951	0,891	0,920	1992
NO_ARR	0,762	0,816	0,788	456

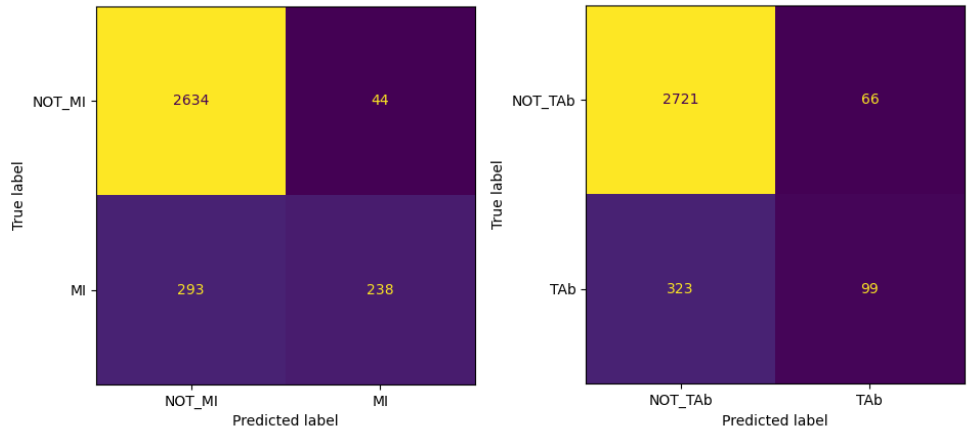

Figure 6.18 Confusion Matrix, ResNet Model, 5 Arrhythmia, Arrhythmia Type: MI, TAb Threshold=0,35

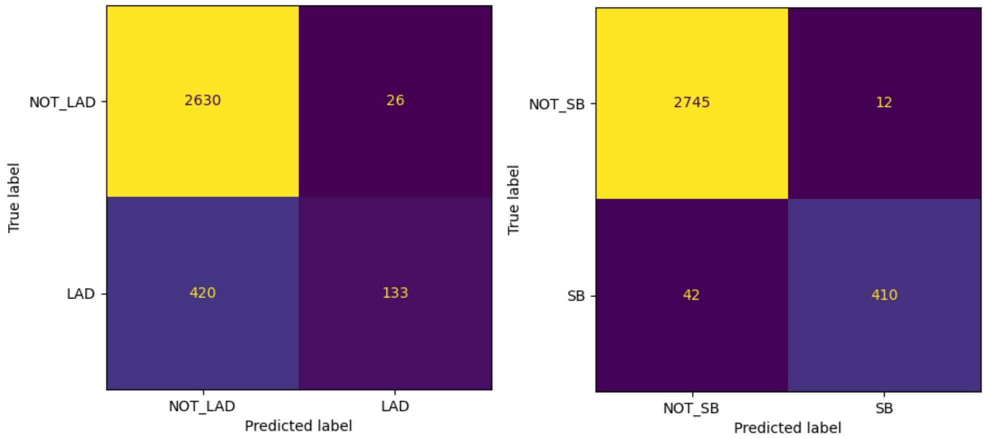

Figure 6.19 Confusion Matrix, ResNet Model, 5 Arrhythmia, Arrhythmia Type: LAD, SB Threshold=0,35

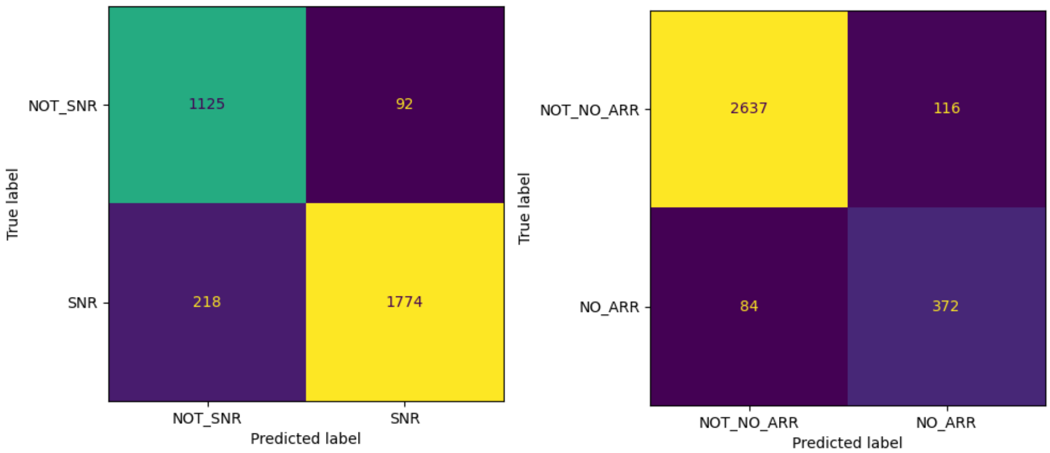

Figure 6.20 Confusion Matrix, ResNet Model, 5 Arrhythmia, Arrhythmia Type: SNR, NO_ARR Threshold=0,35

Table 6.8 ResNet Model, Classification Report, 10 Arrhythmia, Threshold=0,10

	precision	recall	f1-score	support
MIs	0,734	0,585	0,651	217
MI	0,833	0,500	0,625	528
LVH	0,746	0,417	0,535	240
AF	0,802	0,941	0,866	323
TAb	0,527	0,277	0,363	423
abQRS	0,800	0,058	0,109	342
LAD	0,705	0,396	0,507	548
SB	0,900	0,927	0,913	454
SNR	0,936	0,938	0,937	1995
STach	0,865	0,928	0,895	235
NO_ARR	0,642	0,779	0,704	145

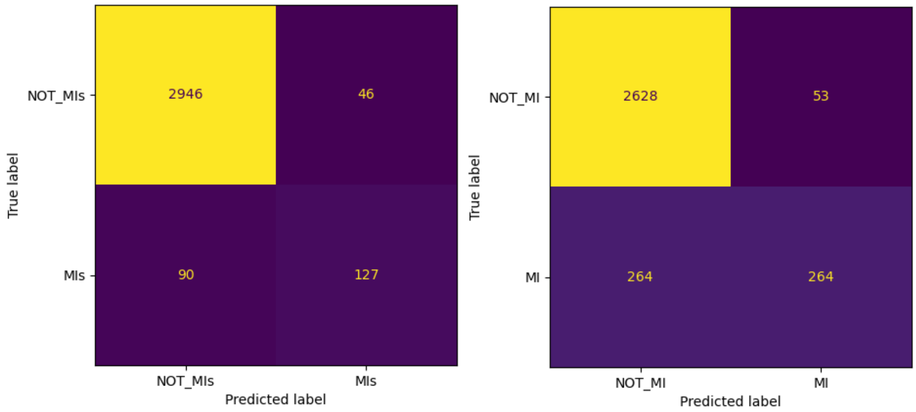

Figure 6.21 Confusion Matrix, ResNet Model, 10 Arrhythmia, Arrhythmia Type: MIs, MI Threshold=0,10

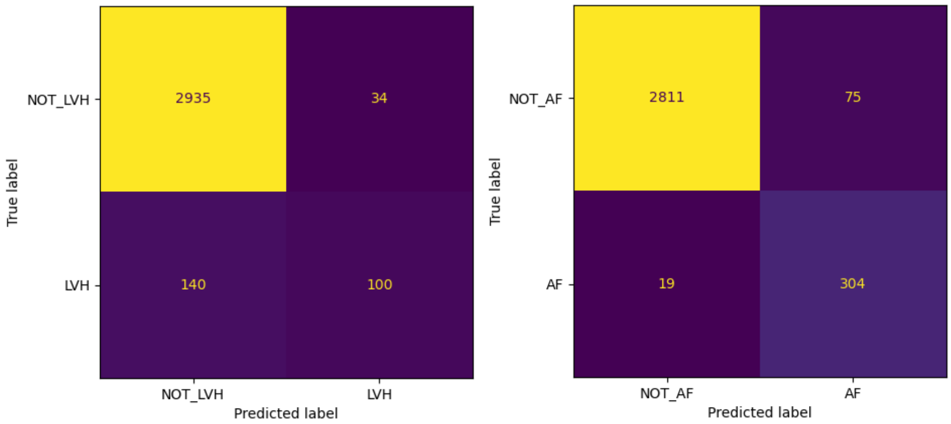

Figure 6.22 Confusion Matrix, ResNet Model, 10 Arrhythmia, Arrhythmia Type: LVH, AF Threshold=0,10

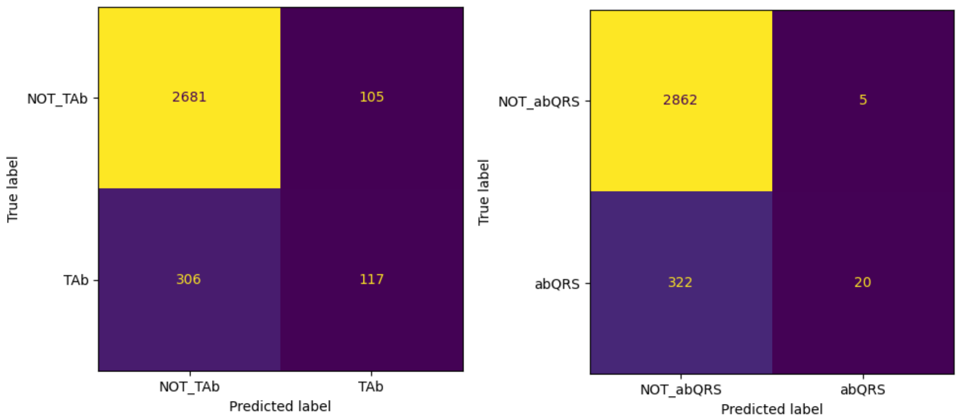

Figure 6.23 Confusion Matrix, ResNet Model, 10 Arrhythmia, Arrhythmia Type: TAb, abQRS Threshold=0,10

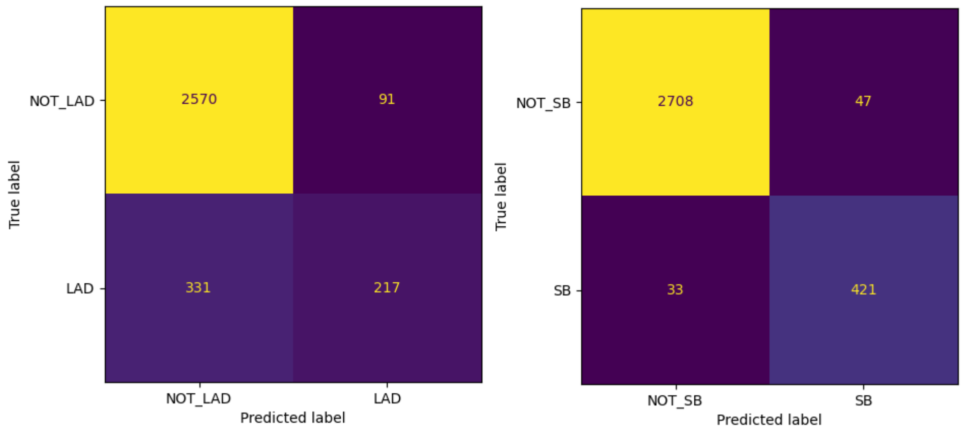

Figure 6.24 Confusion Matrix, ResNet Model, 10 Arrhythmia, Arrhythmia Type: LAD, SB Threshold=0,10

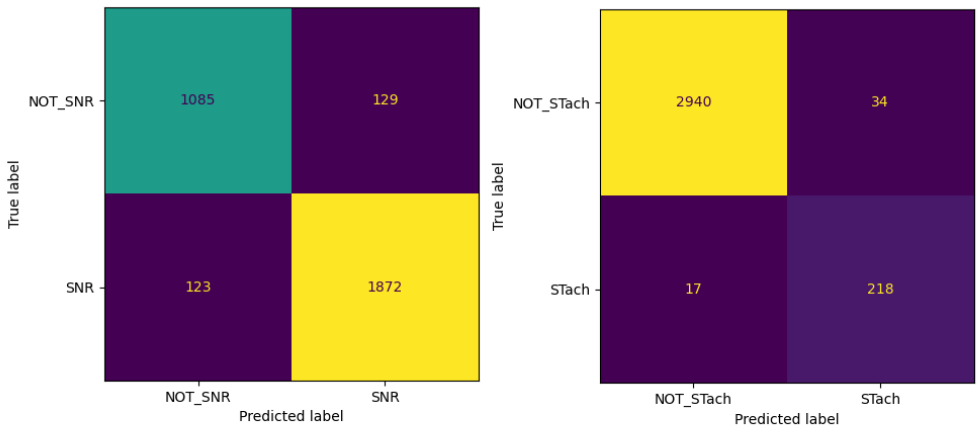

Figure 6.25 Confusion Matrix, ResNet Model, 10 Arrhythmia, Arrhythmia Type: SNR, STach Threshold=0,10

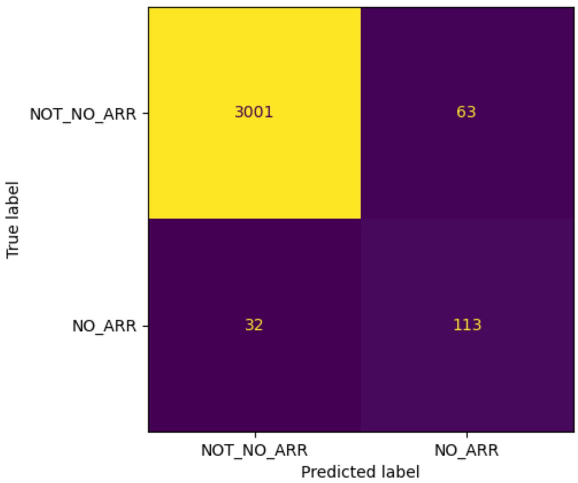

Figure 6.26 Confusion Matrix, ResNet Model, 10 Arrhythmia, Arrhythmia Type: NO_ARR, Threshold=0,10

Table 6.9 ResNet Model, Classification Report, 15 Arrhythmia, Threshold=0,10

	precision	recall	f1-score	support
MIs	0,778	0,527	0,628	226
MI	0,808	0,479	0,602	528
LVH	0,793	0,384	0,518	250
VEB	0,584	0,391	0,469	115
AF	0,796	0,924	0,855	329
TAb	0,561	0,231	0,328	415
abQRS	0,759	0,120	0,207	343
LAD	0,754	0,373	0,499	549
SB	0,909	0,935	0,922	448
SNR	0,939	0,927	0,933	1991
STach	0,893	0,889	0,891	235
NSSTTA	0,483	0,192	0,275	151
STD	0,526	0,076	0,132	132
LAnFB	0,800	0,232	0,360	155
LVHV	0,615	0,246	0,352	130
NO_ARR	0,630	0,789	0,700	123

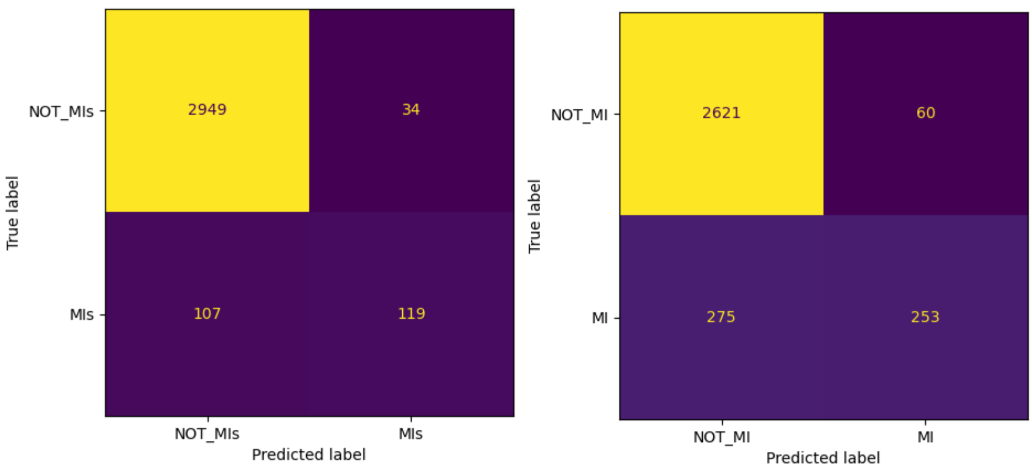

Figure 6.27 Confusion Matrix, ResNet Model, 15 Arrhythmia, Arrhythmia Type: MIs, MI Threshold=0,10

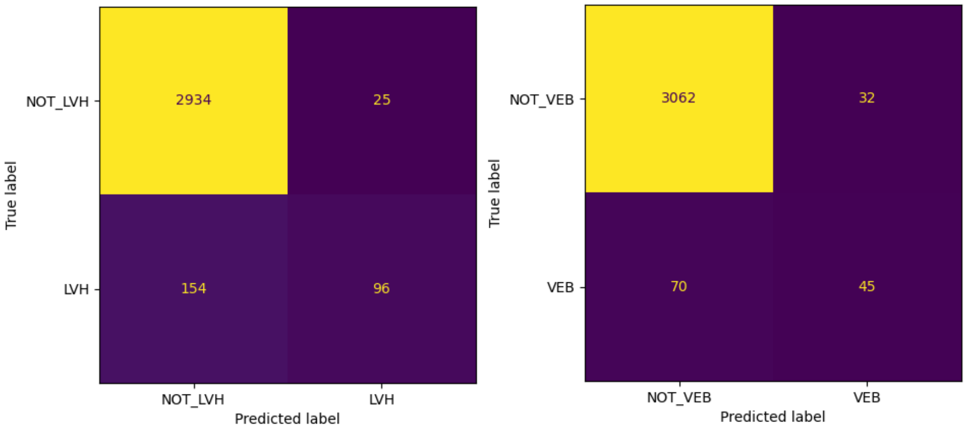

Figure 6.28 Confusion Matrix, ResNet Model, 15 Arrhythmia, Arrhythmia Type: LVH, VEB Threshold=0,10

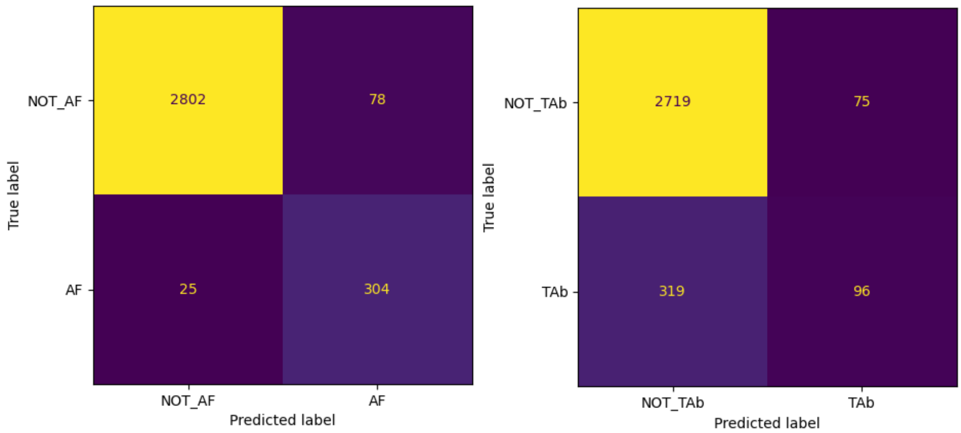

Figure 6.29 Confusion Matrix, ResNet Model, 15 Arrhythmia, Arrhythmia Type: AF, Tab Threshold=0,10

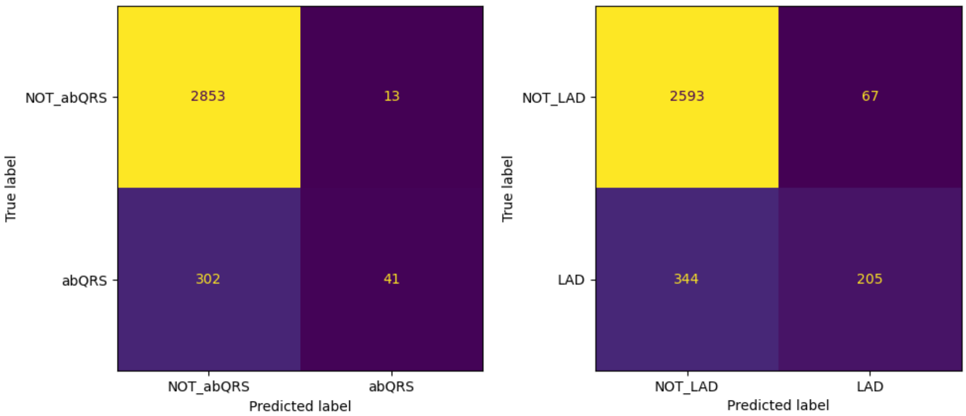

Figure 6.30 Confusion Matrix, ResNet Model, 15 Arrhythmia, Arrhythmia Type: abQRS, LAD Threshold=0,10

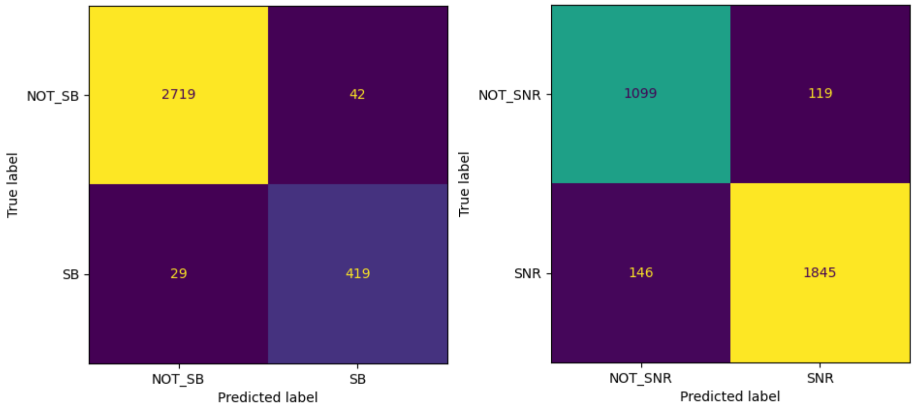

Figure 6.31 Confusion Matrix, ResNet Model, 15 Arrhythmia, Arrhythmia Type: SB, SNR Threshold=0,10

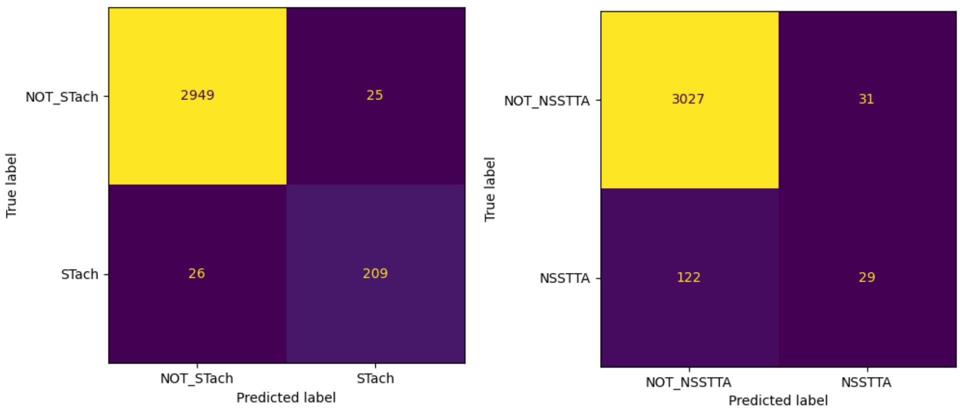

Figure 6.32 Confusion Matrix, ResNet Model, 15 Arrhythmia, Arrhythmia Type: STach, NSSTTA Threshold=0,10

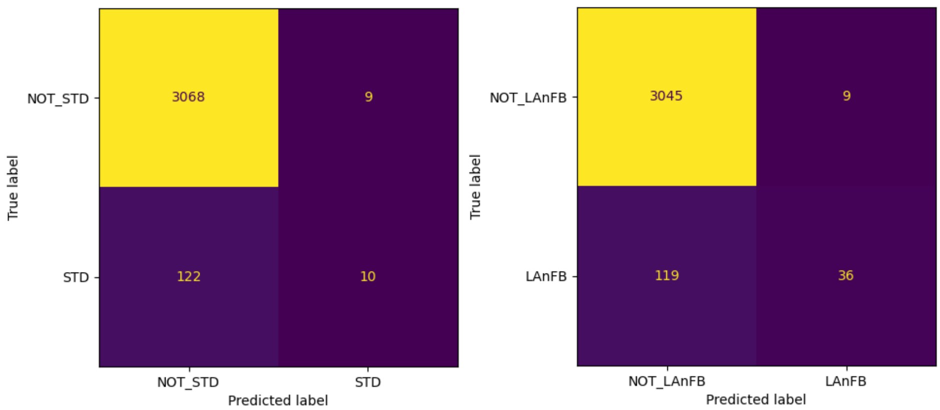

Figure 6.33 Confusion Matrix, ResNet Model, 15 Arrhythmia, Arrhythmia Type: STD, LanFB Threshold=0,10

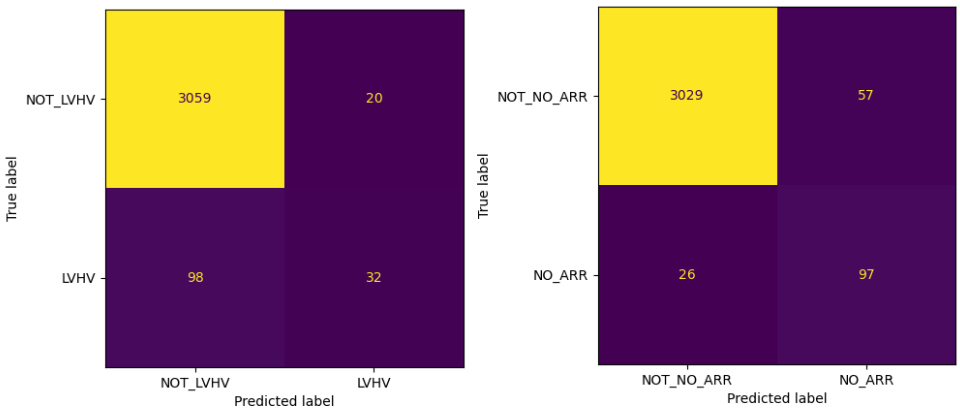

Figure 6.34 Confusion Matrix, ResNet Model, 15 Arrhythmia, Arrhythmia Type: LVHV, NO_ARR Threshold=0,10

6.3 Weight Function

The weight function is of great importance in achieving these success rates of the models. For comparison purposes, experiments were made with different weight functions in multi label training and single label output. In the studies so far, the weight function specified in Section 5.3, Eq. (4) was used. For testing purposes, the weight function in this section Eq. 1 was used and the results in Table 6.6 were obtained.

$$weight[i] = \frac{Number\ Of\ ECG}{2 * bincoun(y\_arr[i])} \tag{1}$$

When looking at the relationship between weight functions, there is a square root operation in the weight function used so far (Section 5.3, Eq. (4)). Having a square root operation enables smoother data to be obtained. Multiplication by 4 is seen as a constant in the denominator. However, looking at Section 6.3 Eq. (1), there is no square root operation. There is 2 in the denominator, not 4. For this reason, this weight function is expected to produce sharper values.

In Table 6.1, the study results can be seen when the FCN model is trained with the weight function in Section 5.3, Eq. (4). If the same network is trained according to the weight function in Section 6.3, Eq. (1) rather than the function in Section 5.3, Eq. (4), the results in Table 6.6 are obtained. The success rates of two different weight functions can be seen in Table 6.6.

Table 6.10 The Effect of Two Different Weight Functions on FCN Model Success

Weight Function	No Square Root Weight Function	Square Root Weight Function	No Square Root Weight Function	Square Root Weight Function	No Square Root Weight Function	Square Root Weight Function
Number of Arrhythmias Studied	5	5	10	10	15	15
No Arrhythmia Class is Available	Yes	Yes	Yes	Yes	Yes	Yes
Total Number of Classes Studied	6	6	11	11	16	16
Number of ECG Recordings Containing No Arrhythmia	4559	4559	1452	1452	1230	1230
Number of ECG Recordings Containing 1 Arrhythmia	17872	17872	16789	16789	14868	14868
Number of ECG Recordings Containing 2 Arrhythmia	7383	7383	7931	7931	7972	7972
Number of ECG Recordings Containing 3 Arrhythmia	2224	2224	3677	3677	4349	4349
Number of ECG Recordings Containing 4 Arrhythmia	46	46	1812	1812	2374	2374
Number of ECG Recordings Containing 5 Arrhythmia	0	0	348	348	1012	1012
Number of ECG Recordings Containing 6 Arrhythmia	0	0	75	75	226	226
Number of ECG Recordings Containing 7 Arrhythmia	0	0	0	0	50	50
Number of ECG Recordings Containing 8 Arrhythmia	0	0	0	0	3	3

Number of Total ECG	32084	32084	32084	32084	32084	32084
Total Number of Unique Combinations	27	27	238	238	813	813
Accuracy Score	**0,864**	**0,878**	**0,888**	**0,899**	**0,89**	**0,90**

The only difference between the models in Table 6.8 is the weight functions. The data sets studied, arrhythmia numbers and everything are exactly the same. The weight function in Section 5.3, Eq. (4) achieved higher success in all comparisons than the one in Section 6.3, Eq. (1). The main reason for this is the square root operation in Section 5.3, Eq. (4). If an arrhythmia occurs frequently in the data set, it is given less weight, whereas if it occurs less often, it is given more weight. What is important here is the coefficient to be applied. With the square root expression, giving too high a weight is prevented, the value is softened, and it is increased at very low weights. Because when the square root operation is applied to numbers between 0-1, the number grows.

When the studies carried out in the thesis study are compared with the studies in the literature, the thesis study stands out with some differences. The 'no arrhythmia' class has been defined to classify ECG recordings that do not contain any arrhythmia. This approach is completely new in the literature. There are studies in the literature where the threshold value method is used to classify ECG recordings that do not contain any arrhythmia [47]. Accordingly, if any arrhythmia in an ECG record does not exceed the threshold value, then the relevant ECG record is evaluated as 'no arrhythmia'. However, it is not explained here how the threshold value is determined. In the thesis study, a success rate of 80% to 90% was achieved with the single-label output approach. This is a very high success rate compared to other studies in the literature. However, if there is more than one arrhythmia in an ECG recording, only one of them can be detected. In this case, the multi-label output approach should be used. In this approach, since it tries to detect all arrhythmias in the ECG recording, the success rate decreases to 48%-62%. It is seen that studies in the literature work on fixed data sets. As a result of this situation, the models produced may be successful in detecting arrhythmias in the studied data set, but may fail to detect arrhythmias in another data set. In the literature, there is a study in which a success rate of 68% was achieved on the trained dataset, while a success rate of 31% was achieved on the foreign dataset [37].

7. CONCLUSION

We performed an arrhythmia classification study on 5, 10, 15 arrhythmias on 32084 ECG records. To prevent the trained models from producing results by relying on a single data set, two different data sets were combined to create a single data set. The results obtained in the studies were taken from the combined data set.

Both FCN and ResNet models were trained and the model successes were shown comparatively. In cases where model successes are shown, the only difference is the network structure, all other conditions are kept the same. In general, the FCN model showed higher success than the ResNet model.

The effect of using different weight functions on model success has been shown. When two different weight functions are compared, it is seen that the weight function containing square roots (Section 5.3, Eq. (4)) achieves higher success due to its smoothing feature.

The 'no arrhythmia' class has been defined in order to classify ECG recordings that do not contain any arrhythmia. The 'no arrhythmia' class was included in all classification studies. Thanks to this approach, the models can also classify ECG recordings that do not contain any arrhythmia as successful. Defining the 'no arrhythmia' class is a new approach. Defining the 'no arrhythmia' class is an important issue that distinguishes the thesis study from other studies in the literature.

Models were trained separately with both multi-label training, single-label output and multi-label training, multi-label output approach. While success rates between 80% and 90% were achieved in the multi-label training and single-label output approach, success rates of 46-62% were achieved in the multi-label training and multi-label output approach. Threshold approach was used to produce multi-label output. While all other conditions are the same, the effect of changing only the threshold value on the model success is shown comparatively. In the FCN model, the ideal threshold value for all scenarios is fixed and this value is 0.55. In the ResNet model, there are differences in the ideal threshold value. The ideal threshold value is 0.35 when working with 5 arrhythmias, and 0.10 when working with 10 and 15 arrhythmias.

There are arrhythmia classification studies in the literature with higher success rates than the current thesis study. However, these success rates were generally obtained on a single data set. There is a study in which the success rate decreased from 68% to 31% when the same study was conducted on a different data set [37]. The results obtained in the thesis study, unlike the results in the literature, were obtained by combining two different data sets. This approach is an important issue that distinguishes the thesis study from the studies in the literature.

There are more than 100 types of arrhythmias. While some of these are quite common, some are quite rare. Highly trained personnel are needed to examine the ECG recordings and make the correct diagnosis of arrhythmia. This study may facilitate cardiologists in classifying arrhythmias.

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