ECG Signals Classification

Signals Processing Project

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Abstract

Electrocardiogram (ECG) signals serve as a cornerstone in the diagnosis and monitoring of cardiovascular diseases, offering a non-invasive method to analyze the heart's electrical activity. With the rapid advancement of machine learning and deep learning methods, automating ECG classification has become increasingly viable, enabling faster and more accurate diagnoses. This study focuses on classifying ECG signals using the dataset with ECG signals and evaluates the performance of the machine learning approach.

Introduction

Background and Motivation

Cardiovascular diseases remain the leading cause of mortality worldwide, necessitating timely and accurate diagnostic tools. The electrocardiogram (ECG), a widely utilized diagnostic modality, captures the electrical activity of the heart and provides essential information for identifying conditions such as arrhythmias, myocardial infarction, and heart block. However, manual interpretation of ECG signals is both time-intensive and prone to inter-observer variability, motivating the development of automated classification systems.

Project Goals and Objectives

This study aims to develop an ECG classification system using the ECG dataset. Specific objectives include:

1. Conducting an exploratory data analysis (EDA) to examine signal characteristics and dataset composition.
2. Reviewing existing literature to understand the current state-of-the-art approaches.
3. Designing and implementing machine learning model, with a focus on deep learning techniques.
4. Analyzing the results and proposing future research directions for enhanced ECG diagnostics.

Materials and Methods

Dataset Overview

The **PTB-XL dataset**, published by PhysioNet, is the largest open-access resource for ECG signal analysis. It contains 21,799 ECG records, each 10 seconds length, from 18,869 patients, where 52% are male and 48% are female. The data are recorded using 12 leads at two sampling frequencies—500 Hz and 100 Hz—offering flexibility for both high-resolution analysis and computational efficiency. For this research 5 superclasses are used and signals with 500 frequency rate.

Number of records	Superclass	Description
9514	NORM	Normal ECG
5469	MI	Myocardial Infarction
5235	STTC	ST/T Change
4898	CD	Conduction Disturbance
2649	HYP	Hypertrophy

Literature Review

Investigating most recent, cited and additional literature about classification ECG and using PTB XL dataset there is a description of their methods and approaches.

1. **Self-Supervised Learning with Transformers**:
   ECG signals are preprocessed using techniques like bandpass filtering to remove noise and PQRST feature extraction to isolate key segments of the ECG waveform. Data augmentation (e.g., time-shifting and scaling) also helps in improving model robustness by increasing the variability in the training data. A self-supervised learning approach has recently been explored for ECG classification, leveraging Masked Autoencoders (MAE) in combination with Transformer architectures. This method involves

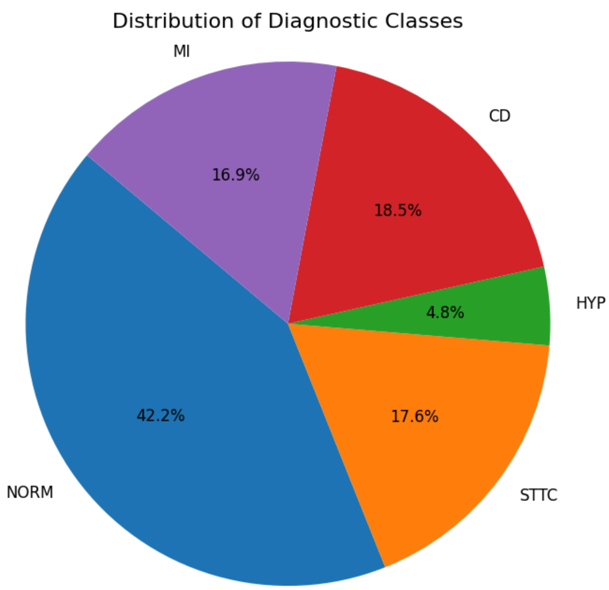
pre-training a model on ECG signals where random portions of the input data are masked, and the model learns to predict the missing segments. The advantage of this approach is that it allows the model to learn meaningful representations from ECG data without requiring labeled data during pre-training. After the self-supervised pre-training phase, the model is fine-tuned using labeled data to perform ECG classification. Transformers are employed due to their ability to capture long-range dependencies in sequential data, which is essential for the temporal nature of ECG signals. This approach has shown significant improvements in the model's ability to generalize to unseen ECG signals, particularly for complex classification tasks

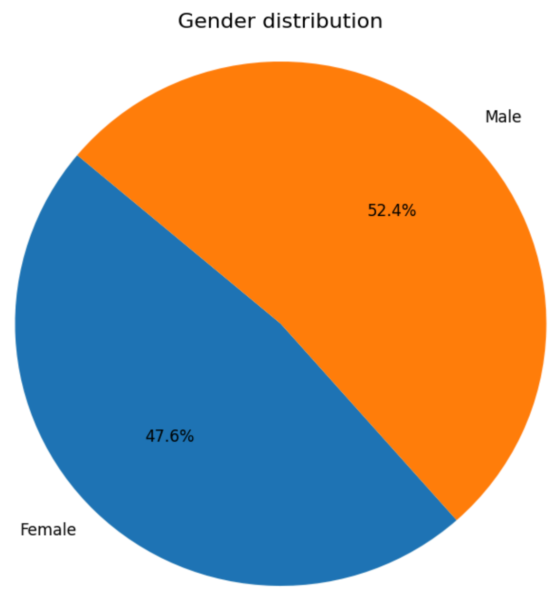
2. **Deep Learning Approaches**:
   Some studies have focused on utilizing traditional deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for ECG classification. These models are particularly effective because they can extract both spatial and temporal features from ECG signals. CNNs are employed to learn spatial patterns from the raw ECG waveform, while LSTMs are used to capture the temporal dependencies, which is crucial for sequential data such as ECG. In some implementations, CNNs and LSTMs are combined to leverage both types of features. This hybrid approach allows for better recognition of complex ECG patterns, such as those associated with arrhythmias and other cardiovascular conditions. These models have been used successfully on the PTB-XL dataset to classify ECG signals into predefined categories
3. **Transfer learning**:
   Transfer learning has also been applied to ECG classification, particularly through the use of pretrained models such as ResNet and VGG. These models, originally trained on large image datasets like ImageNet, are fine-tuned for ECG classification tasks by adapting them to the PTB-XL dataset. The primary advantage of transfer learning is that it allows the model to leverage features learned from large-scale datasets, reducing the need for extensive labeled ECG data and improving model performance, especially when training data is limited. Transfer learning has been used in various studies to enhance the performance of ECG classification models by fine-tuning the last layers of the pretrained networks to specifically identify ECG-related features

EDA

Preliminary EDA was conducted to investigate data in a more detailed way.

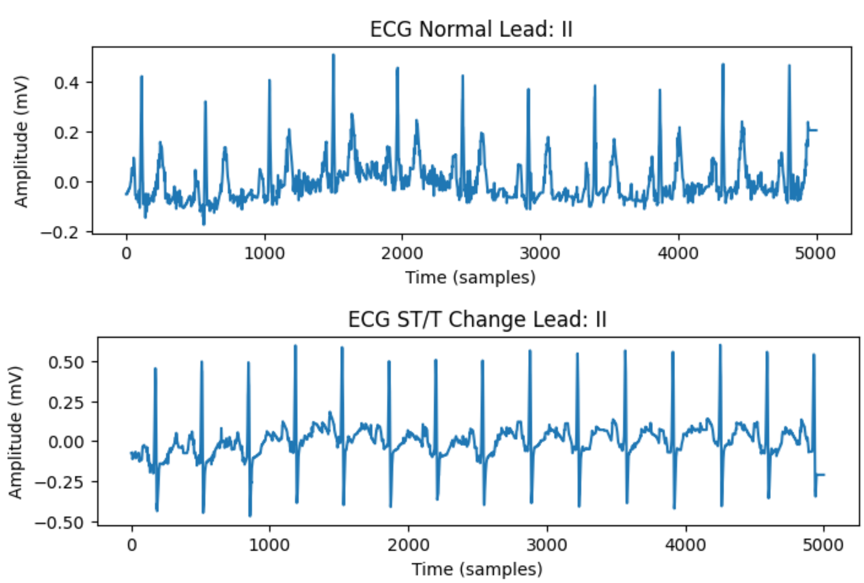
However, not all of them are labeled, and not all the labels are assigned 100% certainty. Both cases were filtered out. The remaining records had classes and subclasses assigned to them. This action resulted in the collection of 16,966 ECG records

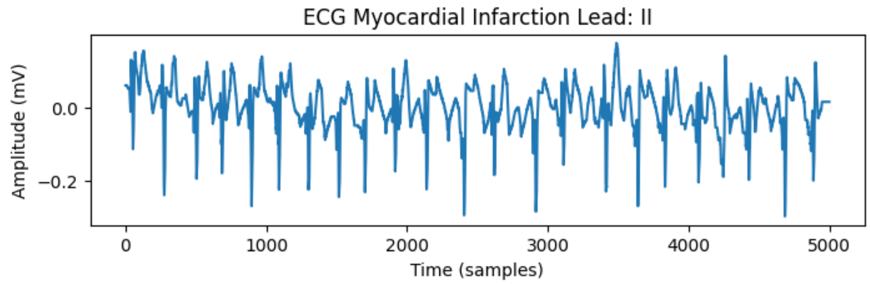


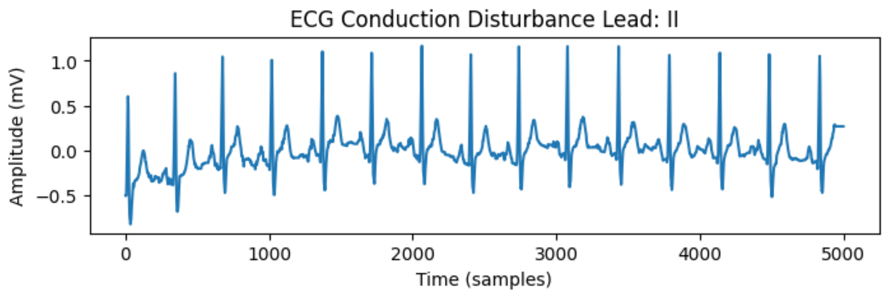


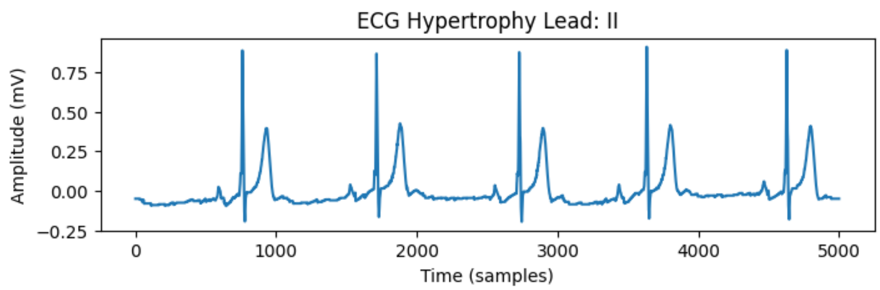
By exploring data, it became clear that the data was quite well collected, especially for machine learning. It is a balanced dataset for binary classification at first glance and balanced by gender.

Examples of second lead for different ECG diagnosis



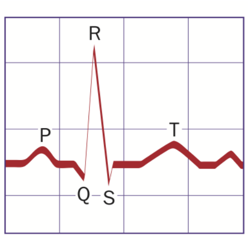






Author's Approach

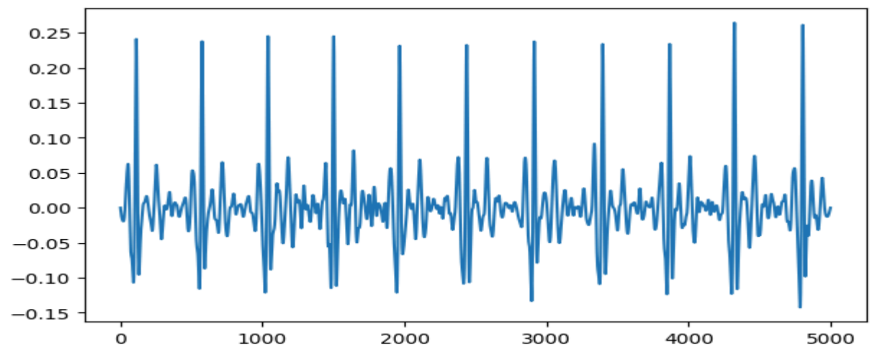
The primary goal of this project is to classify ECG signals using a deep learning-based approach. Each ECG signal contains 12-leads (12 signals per ECG signal) which results in total 16,966 ECG signals * 12 channels = **203,592 separate signals**. As was described above and in references, key features for ECG signals contain so-called QRS complexes.



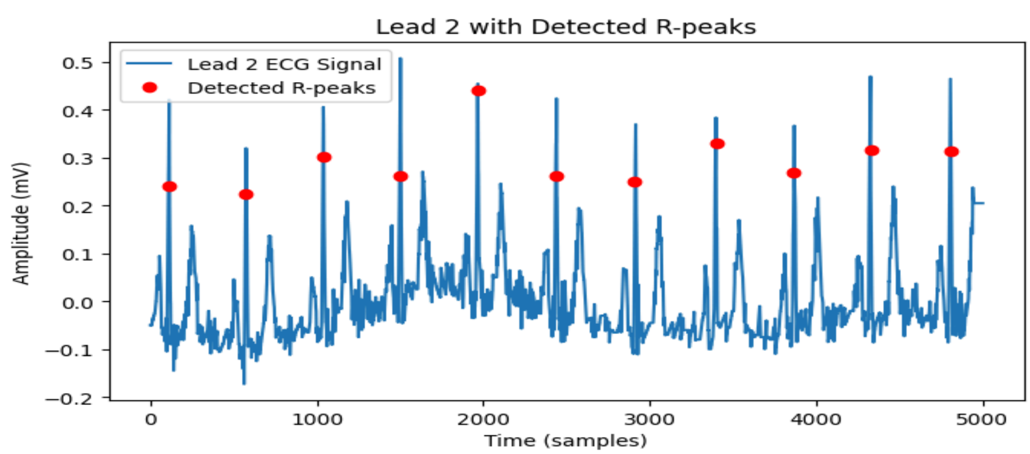
The author decides to process each separate signal to find a **pattern segment** for each of them. Having this vectors of patterns of whole ECG signal (12 channels) it is processed with CNN classifier then. Pipeline consist of next steps:

1. Filter each separate signal
2. Detect R-peaks in second lead
3. Segment QRS complexes with window size within R-peaks in each separate signal
4. Cut each separate signal into segments
5. By averaging segments in each separate signal, get general pattern segment for each separate signal and resample to have equal length
6. Feed these segments into classifier (CNN)

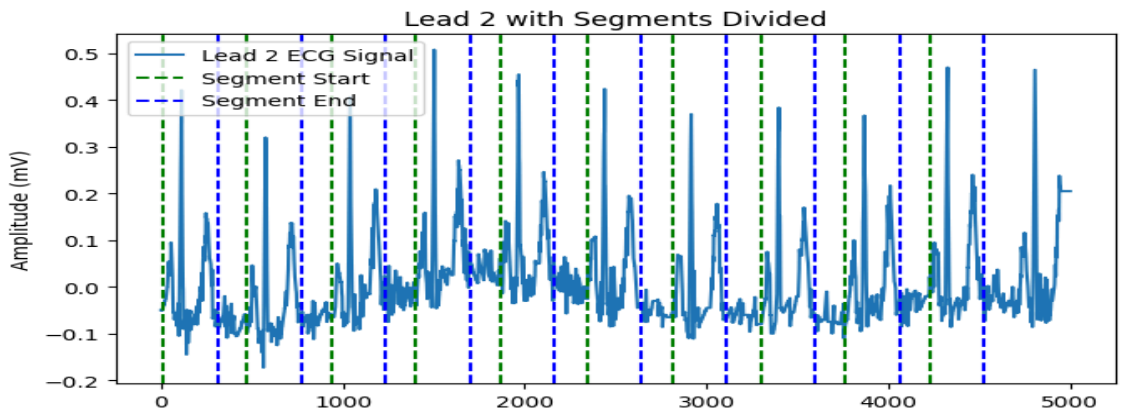
For filtering was used **bandpass Butterworth filter** (5-20 Hz) to remove baseline wander in in ECG signals.

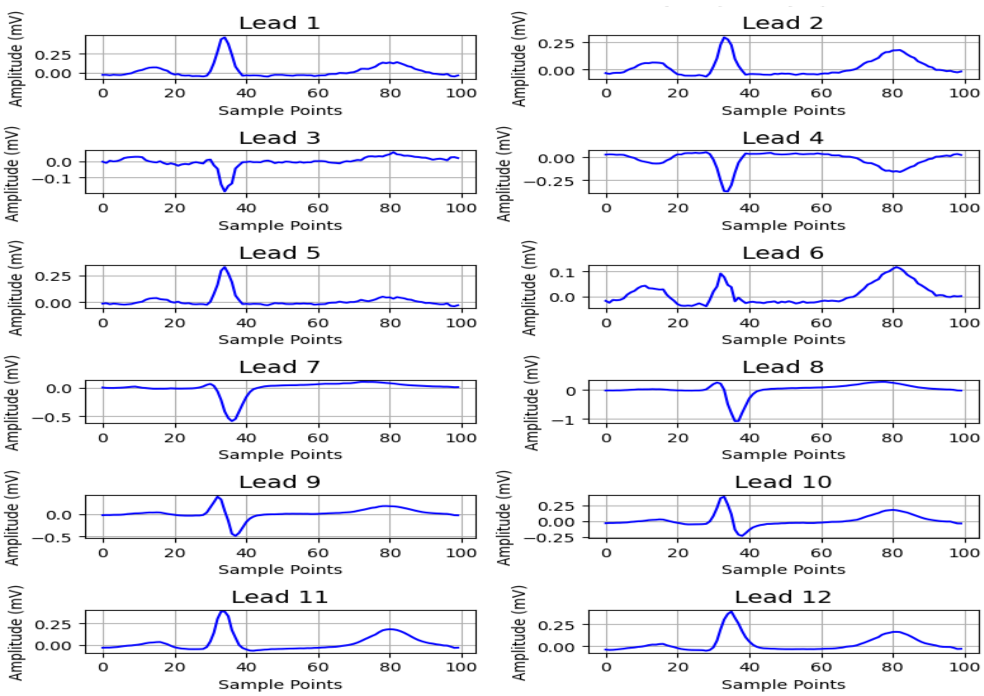


For R-peaks detection was used **Pan-Tompkins** algorithm which involves filtered signal to differentiation, squaring, and moving window integration to highlight R-peaks. The R-peaks themselves were identified by finding all local maxima by simple comparison of neighbouring values using a threshold with scaled maximum amplitude in integrated signal.



Indexes of R-peaks was detected on **second lead** since it is showing the heart's natural rhythm. Then having this indexes from second lead each separate signal was divided into segments around these peaks with window 200 ms before and 400 ms after based on human physiology and were extracted. The extracted segments are resampled using interpolation to a fixed size of 100 samples per segment per lead for uniformity because it is necessary to have the same shape for CNN model.





The **average pattern segment** for each separate signal was computed by aggregating all detected R-peak-centered segments in each separate signal

On the output of this processing pipeline for each 12-lead ECG signal was obtained a **vector with shape (100, 12)** where **100 - length of segment**, **12 - channels** (12 different average pattern segments).

The author's idea to get an average pattern segment for each signal was because CNN does not accept different vector sizes. And since each ECG

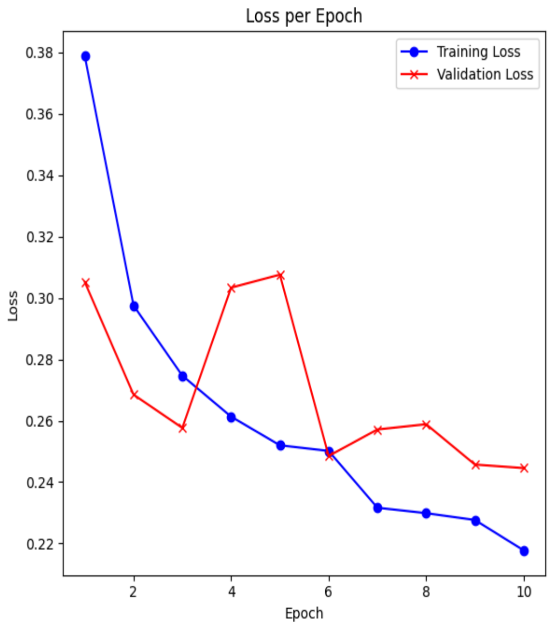
12-lead signal has a different number of QRS complexes, this made it impossible to train the model without any special coding or grouping by the same vector size

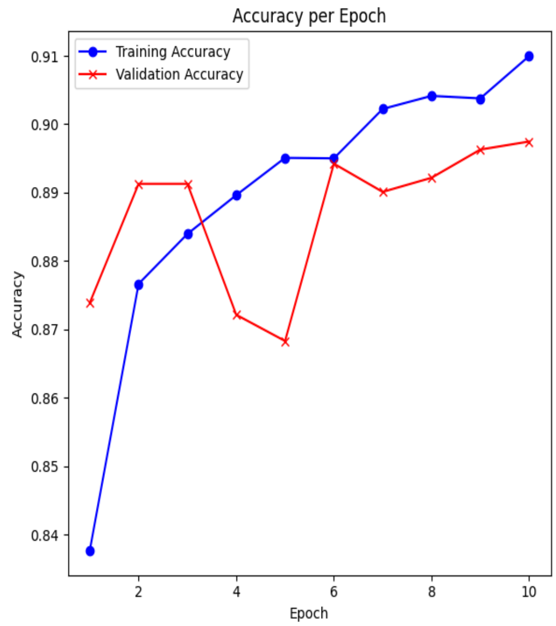
Final step was to build a classifier. The choice was made for CNN. Dataset was split into training and test sets using an 80-20 stratified split, ensuring balanced class representation. Cross-entropy loss and Adam optimizer was used with a learning rate of 1e-3. Two models were trained for **10 epochs with 64 batch size** due to computational time. Main difference in these modes was that one was classifying normal or abnormal ECG, and the other was classifying concrete 5 main superclasses: Normal ECG, Myocardial Infarction, ST/T Change, Conduction Disturbance and Hypertrophy. For this was changed the last layer in the CNN architecture.

2D CNN architecture (number of classes - 2 and 5 corresponding)

Layer type	Details	Output shape
Input Layer	ECG signal segments (1, 100, 12)	(Batch, 1, 100, 12)
Convolutional Layer 1	32 filters, kernel size (3, 3), padding=1	(Batch, 32, 100, 12)
Activation	ReLU	(Batch, 32, 100, 12)
MaxPooling Layer 1	Pool size (2, 2)	(Batch, 32, 50, 6)
Convolutional Layer 2	64 filters, kernel size (3, 3), padding=1	(Batch, 64, 50, 6)
Activation	ReLU	(Batch, 64, 50, 6)
MaxPooling Layer 2	Pool size (2, 2)	(Batch, 64, 25, 3)
Flatten	Flatten the output	(Batch, 64 * 25 * 3)
Fully Connected Layer 1	Linear layer, 128 units	(Batch, 128)
Activation	ReLU	(Batch, 128)
Fully Connected Layer 2	Linear layer, number of classes	(Batch, number of classes)

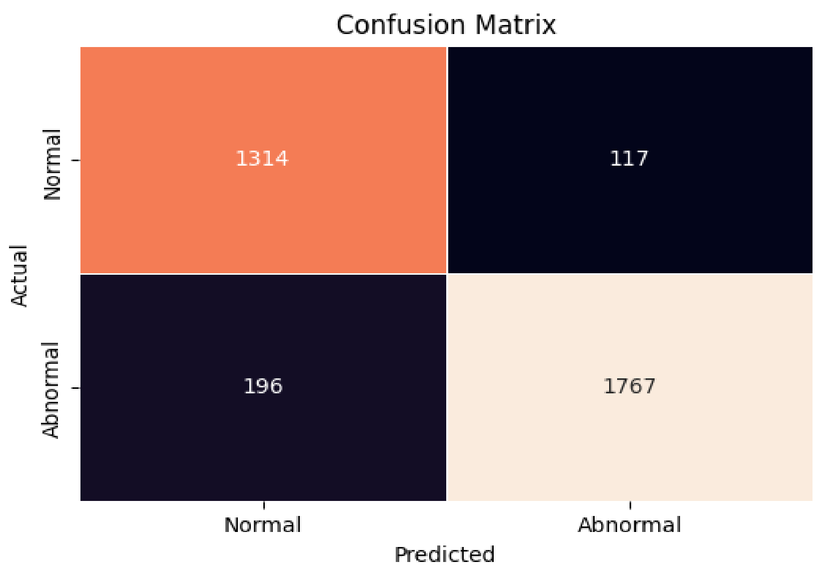
Results



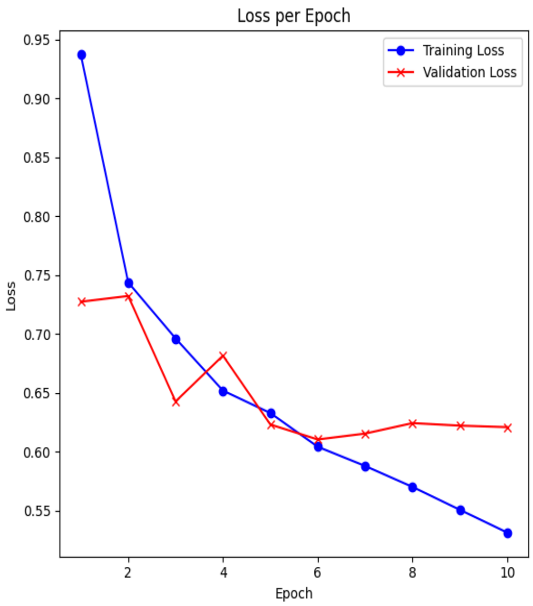


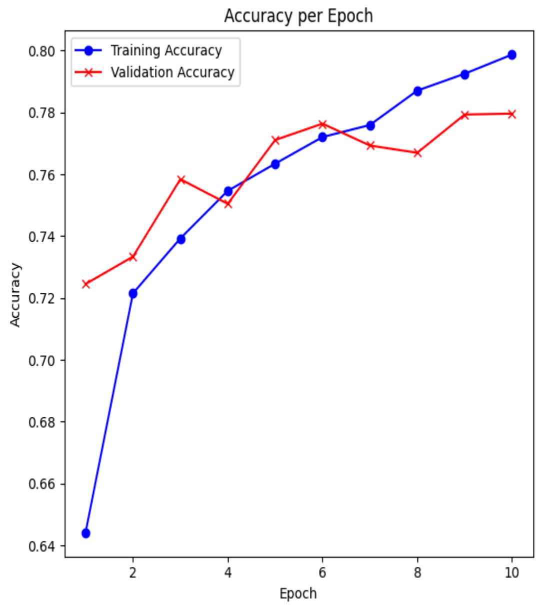
For binary classification CNN model the average test accuracy is **88.67%** and the best is **89.77%**

After saving model and evaluating again in evaluating mode on the **validation set** the final metrics are following **Model validation accuracy is 90.78%**



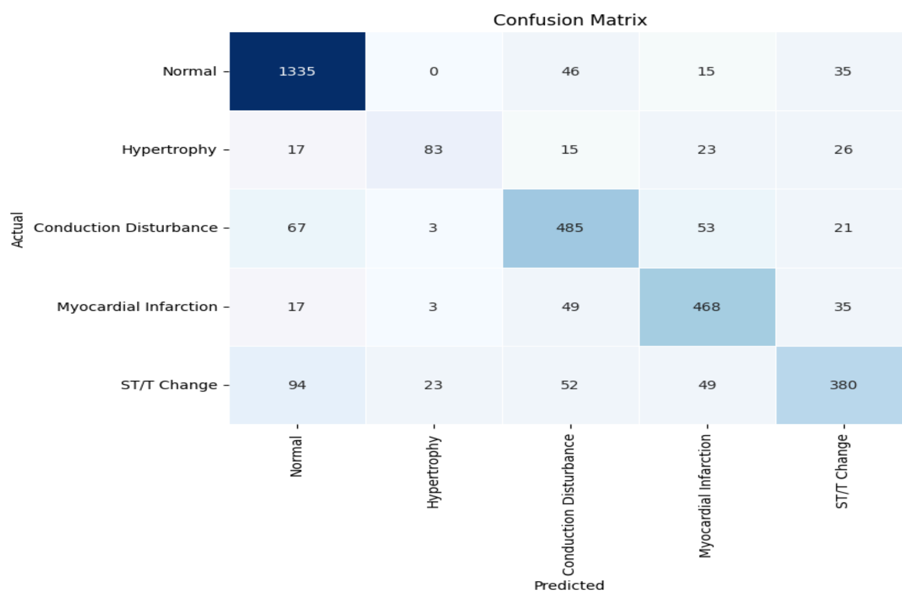
Class	Accuracy
Normal	0.918239
Abnormal	0.900153





For multiclass classification CNN model the average test accuracy is **76%** and the best is **77.53%**

After saving model and evaluating again in evaluating mode on the **validation set** the final metrics are following **Model validation accuracy is 81.05%**



Class	Accuracy
Normal	0.932914
Hypertrophy	0.506098
Conduction Disturbance	0.771065
Myocardial Infarction	0.818182
ST/T Change	0.635452

Discussion

ECG signals are quite sensitive because they are measured using electrode sensors. Any human movement or physical action will be reflected in the ECG signal and may distort it to some extent. Therefore, ECG signals should be measured in very good conditions and in compliance with the following rules

The results were quite surprising and showed how a simple model can achieve good results. This also indicates that QRS complexes carry key information for ECG signals. Analyzing the results for ECG classification of both models it is clear that they are quite good. The model itself is quite simple, and does not consist of any heavy coding or blocks, so it is easy to implement. Comparing the results from other papers, we can say that they do not differ so much in accuracy, although some other authors did much more processing, collected different types of data (such as different types of entropy), used raw signals and processed them, had their metadata collected and computed, and tested many different complex deep networks.

Also, the results showed that accuracy for hypertrophy classification is 50% which is low, like randoming and this is because in dataset was only 4.8% of total ECG signals with hypertrophy diagnosis. It is important to have balanced dataset and further improvement can be to divide dataset, for example, into equal parts, see which class has the minimum number of records and divide the rest by the same number.

Further directions may include the study of the entropy of signals and the entropy of QRS complexes. Additional metadata collection for signals such as heart rate variability (HRV) and beat per minute (BPM) and their study can improve the classification of ECG signals. Also, the right model and its architecture can have a significant impact on improving the results. It is necessary to take into account the fact that a single ECG signal can contain a lot of information for the model: metadata, entropy, QRS complexes. Therefore, it is important that the model architecture handles all this information well. But this raises the problem that all this requires powerful computing power. In the mentioned works, accelerators such as A100 GPU were used, which are specialized for giant datasets and for training neural models. Such accelerators cannot be used in everyday life.

References

Two most cited works:

1. Deep Learning for ECG Analysis: Benchmarks and Insights from PTB-XL by Nils Strodthoff, Patrick Wagner, Tobias Schaeffter and Wojciech Samek, 2020
2. Deep Learning-based ECG Classification on Raspberry PI using a Tensorflow Lite Model based on PTB-XL Dataset by Kushagra Sharma and and Rasit Eskicioglu, 2022

Two most recent works:

1. Masked Transformer for Electrocardiogram Classification by Ya Zhou, Xiaolin Diao, Yanni Huo, Yang Liu, Xiaohan Fan and Wei Zhao, 2023-2024
2. Explainable Deep Learning Based-System for Multilabel Classification of 12-Lead ECG by Yousra Chahinez Hadj Azzem and Fouzi Harrag, 2023

Additional:

1. Deep Learning Techniques in the Classification of ECG Signals Using R-Peak Detection Based on the PTB-XL Dataset by Sandra Śmigiel, Krzysztof Pałczyński and Damian Ledziński, 2021
2. Design and Comparison of Deep Learning Model for ECG Classification using PTB-XL Dataset by Nilankar Bhanja and Prabodh Khampariya, 2023
3. ECG Waveform Classification Based on P-QRS-T Wave Recognition by Muzhir Al-Ani, 2018
4. Pan–Tompkins algorithm