# 12-lead ECG Classification Using Deep Neural Networks

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## Abstract

The electrocardiogram (ECG) is the most widely used diagnostic technique for detecting cardiovascular disease. Manual ECG interpretation, on the other hand, is inefficient and needs highly trained medical professionals. The PhysioNet/Computing in Cardiology Challenge 2020 aims to extract clinical diagnosis from 12-lead ECG data. In this work we proposed deep learning models to classify ECG automatically We will be training our system in 2 phases.We have designed two models, Our first model uses convolutional and max pooling layers for feature extraction, Our second model, which uses a convolutional DNN and produces better results with binary SVMs for classification.

## Related Work

[1] proposes a Residual-CNN GRU neural network with an attention mechanism for categorizing 12-lead ECGs into 24 distinct groups.To identify 27 clinical diagnoses from 12-lead ECGs, a new deep learning model called SEResNet34 was developed by [2].[3] proposes two models, first model is straightforward that can be used as a baseline model, with 5 CNN layers and Model 2 consists of two parallel deep residual neural networks, each with 37 CNN layers.The model with deeper layers outperforms the one with shallower layers in classifying ECG abnormalities. Our Proposed solution is inspired by [4] that uses Residual blocks with skipping connections and then uses SVMs for classification purpose.

## Issues and Challenges

- The early and correct diagnosis of cardiac abnormalities can increase the chances of successful treatments.
- The manual interpretation of the electrocardiogram is time-consuming . It requires skilled personnel with a high degree of training.
- Automatic detection and classification of cardiac abnormalities can assist physicians in the diagnosis

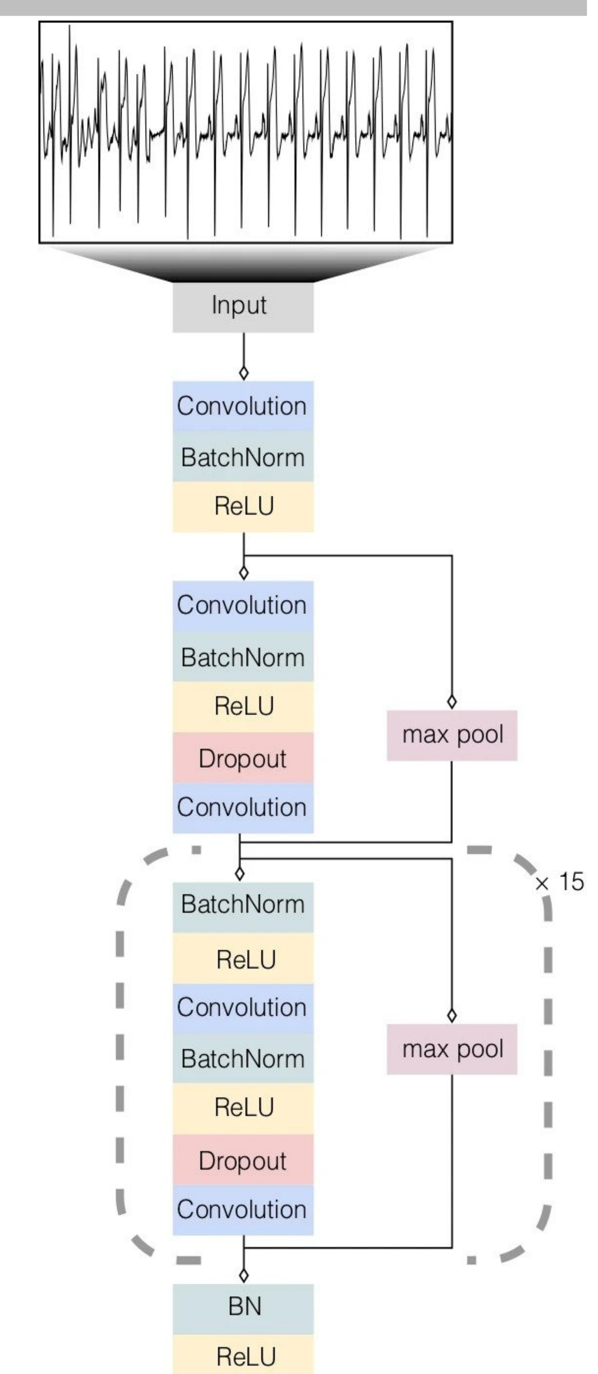
## Dataset

We used data from 5 different sources. Two sources were divided into training, validation, and test sets; two sources were included just as training data; and one source was included only as test data. The 12-lead ECG recordings were obtained in clinical environment. We have chosen Frame length of 15000. i.e. Sample rate * mean time length.For further pre-processing, Inversion were removed if spotted, Each Frame were Normalized , we also filtered the Bandpass (To remove the extremely high or low amplitude). The Signals were also Padded or truncated accordingly.

| Dataset | Sample freq.(Hz) | Duration (s) | Num. of records |
|---|---|---|---|
| PTB-XL | 500 | 10 | 21837 |
| CPSC-Extra | 500 | 10 - 98 | 3453 |
| CPSC | 500 | 9 - 118 | 6877 |
| PTB | 1000 | 38.4 - 120 | 516 |
| Geogia | 500 | 10 | 10344 |
| StPetersburg | 257 | 1800 | 74 |

## Methodology

We have proposed two models to classify ECG diagnoses over a broad range of frequent and essential diagnoses. Our first model uses convolutional and max pooling layers stacked together for feature extraction. Our second model uses convolutional Deep Neural Network that is made up of 16 residual blocks , each having two convolutional layers. Our second model gave better results then our first model. The architecture of our second model can be seen. For classification purpose we have used binary SVMs. We will use the output of the last layer, before dense layers, as the output of feature extractor and input to binary SVMs for one-vs-rest classification.For this purpose, the dataset will be organized in such a manner that each binary SVC has data from its main class with positive labels and data for all other classes joined together in the form of negative class.




## Experiments and Results

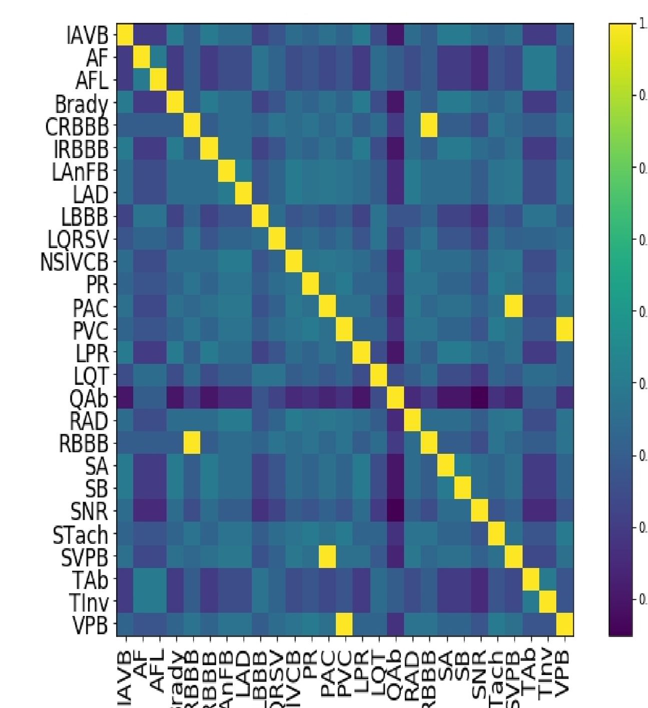
| Proposed Models | | | | | |
|---|---|---|---|---|---|
| **Models** | **AUROC** | **AUPRC** | **Accuracy** | **F_measure** | **F-beta measure (beta=2)** |
| **Model 1** | **0.820775** | **0.342646** | **0.009588** | **0.342446** | **0.465158** |
| **Model 2** | **0.88942** | **0.42899** | **0.05172** | **0.398659** | **0.566569** |

## Evaluation Metric Scores

A new scoring methodology was created as an evaluation metric for this years challenge in which misdiagnosis deserves some credit that result in the same diagnosis as the real diagnosis, as determined by the cardiologists. The columns representing the actual label and columns and rows representing the predicted label.

| Models | Scores |
|---|---|
| [1] | 0.659 |
| [2] | 0.653 |
| [3] | 0.546 |
| Model 1 | 0.500445 |
| Model 2 | 0.566569 |

**Comparison with other Models**




**Evaluation metric**

## Conclusion and Futurework

We have designed two models in which we received a challenge score 0.50044 for our model 1 and 0.56656 for model 2. For the futurework, we will resample all data points at a frequency of 500 hz and train on the whole dataset. We can do Support Vector Machine hyperparameter tuning, introduce noise to try to augment the data, and try Resnet or attention-based Convolutional Blocks as proposed in reference papers.

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