**12-lead ECG Classification Using Deep Neural Networks**

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**Abstract**

data and a well-defined analysis, which have hinderedthegeneralizability to classify 12-lead ECGs [10].

**The electrocardiogram (ECG) is the most widely used**

**diagnostic technique for detecting cardiovascular**

We will be using PhysioNet/Computing in Cardiology

**disease. Manual ECG interpretation, on the other hand,**

Challenge 2020 dataset that comprises over 43,000ECG

**is inefficient and needs highly trained medical**

records with diagnostic labels [11], this studyattemptsto

**professionals. The PhysioNet/Computing in Cardiology**

construct a robust model that automaticallydetects cardiac

**Challenge 2020 aims to extract clinical diagnosis from**

abnormality in each 12-lead ECG recording. Thegoal of

**12-lead ECG data. In this work we proposed deep**

this project is to create a technique for diagnosingcardiac

**learning models to classify ECG automatically We will**

anomalies from 12-lead ECGs using a deep neural network.

**be training our system in 2 phases.We have designed**

**two models, Our first model uses convolutional and**

**2. Related Work**

**max pooling layers for feature extraction, Our second**

In [12], a modified residual convolutional network-based

**model, which uses a convolutional DNN and produces**

technique is applied. The split attention block is introduced

**better results with binary SVMs for classification. We**

in the modified residual network to improve the abilityof

**have used a Frame length of 15000. For each of the**

significantly convolutional networks to represent features.

**scored classes a separate SVC was created. Each SVC**

A network architecture based on stages is usedtoprovidea

**was trained in the form of 1 vs rest classifier. The**

better way for information to pass through the network's

**results indicate that automatically categorizing 12-lead**

**ECGs has significant application value. 1. Introduction**

layers.[13] proposes a Residual-CNNGRUneural networkwith an attention mechanism for categorizing12-leadECGs into 24 distinct groups.

The 12-lead ECG is important in clinical diagnostics,

To identify 27 clinical diagnoses from12-lead ECGs, anew

involving arrhythmias and other cardiac disorders. Early

deep learning model called SEResNet34 was developedby

diagnosis and identification of cardiovascular issues can

[14]. A 34-layer ResNet was created for classification

greatly improve the likelihood of effective treatment.

purpose. The design contains 17 sequential skip

connections to boost the efficiency of traditional CNN. The

Over last few years there has been an increase in the

identical processes were carried out in each block.

number of attempts to detect 12-lead ECG clinical

diagnosis, mostly using classic machine learning

[15] proposes two models, first model is straightforward

approaches that need considerable data pre-processing,

that can be used as a baseline model, with 5 CNNlayersand

feature selection, or handmade rules [1-2].Deep-learning

a smaller receptive field. It is incapable of extractingand

algorithms such as Convolutional Neural Networks

identifying complicated features. Model 2 consists oftwo

(CNN) , Recurrent Neural Network (RNN) , Residual

parallel deep residual neural networks, each with37CNN

Neural Networks (ResNet) and their combinations are

layers.both models took ECG data with variedlengths.The

now used in state-of-the-art algorithms for ECG

model with deeper layers outperforms the onewith

categorization[3-9].

shallower layers in classifying ECG abnormalities.

There are, however, limited research on the classification of 12-lead ECGs. This might be because of lack of sufficient

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**3. Data Pre-Processing 3.1. Data Insights**

case of similar classes. The reason for usingSVMsisbecause they have performed really well for ECGclassification [17][18] in the past if the ECGsignal hasbeen compressed to lower dimensions which inour case

We used data from 5 different sources. Two sources were

will be the output of the feature extractor trainedinphase

divided into training, validation, and test sets; two sources

one.

were included just as training data; and one source was

**4.1 Evaluation Metric**

included only as test data. The 12-lead ECG recordings

were obtained in clinical environment.The specifics of data

A new scoring methodology was created as anevaluation

collection differ depending on the source of the databases,

metric for this years challenge in which misdiagnosis

which were compiled all around the world. The label's

deserves some credit that result in the same diagnosisasthe

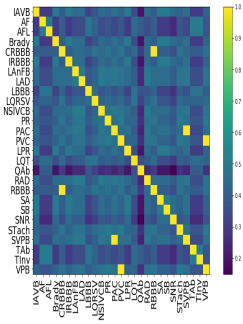
quality was determined by clinical or research methods,

real diagnosis, as determined by the cardiologists. Figure3

and machine generated labels were Over-read by a solo

cardiologist and evaluated by multiple cardiologists. **3.2. Pre-Processing**

depicts the Reward matrix Wfor the Challenge diagnoses.

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.

**4. Proposed Solution**

We have proporsed two models to classify ECG rhythm

diagnoses over a broad range of frequent and essential

diagnoses. Our first model is based on 1-dimensional

convolutional and max pooling layers stacked together for

feature extraction, Our second model, which uses a

convolutional DNN and raw ECG data as input, produces

better results [16] .And then for classification purpose we

have used binary SVMs. We will be training our system in

2 phases.

So In the first phase, we train our first model using

complete CNN with dense layers towards the end and for

our second model we use DNN that is made up of 16

residual blocks, each having two convolutional layers.The

architecture for our models can be observed in figure 1 and

2. In the second phase, we will use the output of the last

layer, before dense layers, as the output of feature extractor

and the 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

**Figure 3: The Reward matrix Wfor the diagnosis**

with positive labels and data for all other classes joined

**scored in the Challenge, with columns representing**

together in the form of negative class. In this manner, each

**the actual label and columns and rows representing**

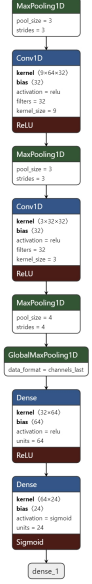
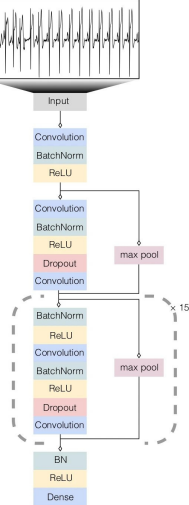
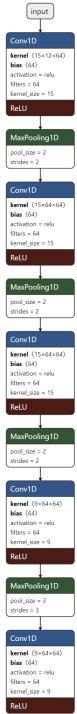
SVC will be able to distinguish one of the classes from the

rest.

**the predicted label.**

The main reason for using binary classifiers towards the end is because this is a multi-class multi-label problem in which most of the classes have similar patterns and initial experimentation reveals sigmoid does not perform well in

2

**Figure 2: Model 2 Architecture Figure 1: Model 1 Architecture**

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**5. Experiments**

**6. Conclusions**

Table 1 illustrates the model's performance on the testing

We have designed two models Our first model is basedon

set. We also compared the scores of the best papers

1-dimensional convolutional and max poolinglayers

submitted for this challenge with our proposed models

stacked together for feature extraction, Our secondmodel,

using their challeneg metric. As shown in the table, our

uses a convolutional DNN with Resnets blocksand,

Model 2 model with deep neural networks and REsnets

produces better result. These geatures are fedintobinary

blocks outperformed the model with CNN and pooling

SVMs for classification. . We received a challengescore

layers as feature extractor.

| **Models** | **Challenge Metric Scores** |
| --- | --- |
| **[12]** | **810.00000**0.685 |
| **[13]** | 0.659 |
| **[14]** | 0.653 |
| **[15]** | 0.546 |
| **Proposed** | **Model 1**  0.500445 |
| **Proposed** | **Model 2**  0.566569 |

0.50044 for our model 1 and 0.56656 for model 2. Forthefuturework, we will resample all data points at a frequencyof 500 hz and train on the whole dataset. WecandoSupport Vector Machine hyperparameter tuning, introducereference papers.

noise to try to augment the data, and tryResnet orattention-based Convolutional Blocks as proposedin

**Table 1: Performance of proposed models on the official test set.**

Table 2 compares the accuracy and other characteristics of both models, revealing that our model 2 produces better accuracy and evaluation results.

| **Proposed**  **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 |

**Table 2: Evaluation metrices for our Proposed Models**

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