

Deep Learning ECG Classification with Discrete Wavelet Contributions

B. Godinho, and J. Rodrigues

Abstract—Deep Learning has been an important technique in helping the classification of electrocardiograms (ECG), allowing a more accurate detection and diagnosis of different cardiovascular diseases. Using the discrete wavelet transform (DWT) it's possible to extract the ECG signal characteristics, for training a Deep Learning Method. DWT is a technique capable of decomposing the signal into different frequencies, thus detecting information regarding time and frequency of the signal. With the combination of these two techniques, it's possible to extract important characteristics of the ECG signal, at different scales, that allow the accurate identification of cardiovascular diseases, such as arrhythmias.

The combination of deep learning and DWT holds great potential to expand and advance the field of ECG analysis and enabling more efficient and accurate diagnosis of cardiovascular diseases. This paper presents an overview of methods for ECG signal classification using Deep Learning with the contribution of the DWT.

Keywords—Arrhythmias, Deep Learning, Discrete Wavelet Transform.

I. INTRODUCTION

According to the World Health Organization (WHO) cardiovascular diseases are the leading causa of death globally and, according to the Directorate General of Health, one in three Portuguese die of cardiovascular disease, which corresponds to about thirty-five thousand deaths per year. [1]

The electrocardiogram (ECG) is a non-invasive way of acquiring the electrical events that occur during the cardiac cycle, where each event has an associated waveform. Surface ECG and electrophysiological studies together provide the essential tools in cardiac electrophysiology, i.e., in detecting and diagnosing electrical abnormalities of the heart and subsequently monitoring the effectiveness of treatment. Thus, since the ECG is the best method for assessing cardiac function, it is essential for the detection of cardiac abnormalities, such as arrhythmias. [2]

The detection and diagnosis of cardiovascular diseases depends on the extraction and classification of heartbeats, requiring the reading and analysis of the different constituents of the cardiac cycle and, since the signal is not stationary, using wavelets we can obtain a more accurate representation of the signal characteristics in different time scales. With the

wavelet transform it is possible to pre-process the signal in order to remove noise and possible artifacts, using filters to extract an ECG signal within desired frequency ranges, with the possibility of different levels of detail. This is an important step in the clinical preparation of the signal for dissecting the signal, since the signal extracted after the application of the transform will correspond to a signal without artifacts or noise. The signal obtained after the application of the filters is decomposed in order to extract the various ECG specific features intended to be analyzed. [3], [4]

Deep Learning is an important method for the classification of ECG signals, since the manual analysis of this signals can be time-consuming and subjected to human error. Thus, Deep Learning is a tool to optimize the classification processes. [2]

II. MATERIAL AND METHODS

A. Data Acquisition and Preprocessing

For this work, we begin by taking the free MIT-BIH Arrhythmia Database [5]. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the Arrhythmia Laboratory, from the Boston's Beth Israel Hospital, between 1975 and 1979. Using discrete wavelets, we proceed to the filters definition for the relevant characteristics for the next step: the definition of the deep learning model.

B. Network Architecture Design

For this level we proceed to design a Deep Learning architecture that can effectively extract relevant features from the ECG signals and learn the mapping between the ECG's important labels inputs and the desired outputs. The defined neural network, with three or more layers, allow us to make approximate predictions and additional hidden layers can help to optimize and refine for accuracy.

C. Training and Validation

At this stage we split the dataset into training and validation sets, we trained the Deep Learning model, using the training data, optimizing the model parameters to minimize the discrepancy between the predicted outputs and the ground truth data obtained from traditional simulations. The validation the model is done using the validation set, assessing its generalization and robustness.

D. Verification and Validation

One investigates the verification of the deep learning-based simulations by comparing the results with benchmarks for

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simple test cases. This step helps establish the accuracy and reliability of the proposed approach.

Statistical metrics, such as mean squared error (MSE), correlation coefficients, or error histograms, will be employed to evaluate the accuracy of the predictions.

III. CLASSIFICATION OF CARDIAC ANOMALIES

A. Data Acquisition

For the elaboration of our first deep learning model, we used the data in table I where the ECGs are parameterized and classified as healthy or revealing some pathology. In this first case we use as parameters:

- L1 – Heart rate (beats per minute – bpm)
- L2 – Duration of P wave (milliseconds – ms)
- L3 – Duration of PR interval (ms)
- L4 – Duration of QRS complex (ms)
- Classification: 0= healthy; 1= some pathology

TABLE I
ECG CLASSIFICATION FROM 4 PARAMETERS

ECG Labels					
#	L1	L2	L3	L4	Classification
1	105	137	95	153	1
2	60	110	160	55	0
...
60	230	148	216	140	1
61	72	104	184	85	0

B. Results

Using a 3 layers deep learning, with a hidden layer with 5 neurons, we implement a keras model using 1000 epochs and 150 batch size for the weights determination. [6]

The accuracy of the model determines the percentage of predicted values that match with actual values, if both values are equal, it's considered accurate. In figure 1 is illustrated a representative graph of this function where it's possible to see that the percentage of validation accuracy was higher than the training accuracy, with 94.74% and 90.48%, respectively.

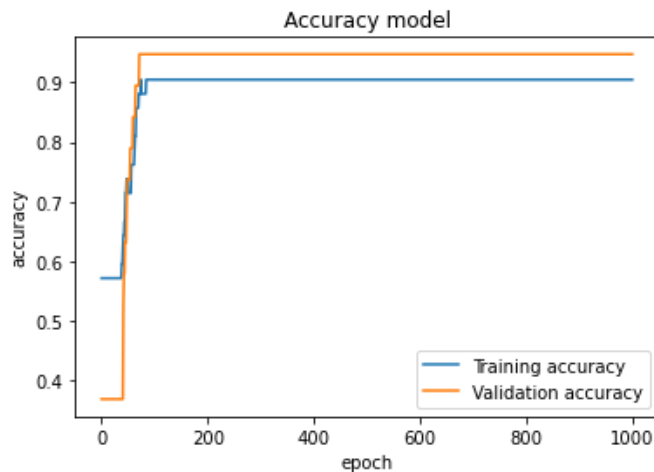


Fig. 1 Accuracy function for the model

With the loss function defined by the equation (1), was possible to extract a representative graph of this function, figure 2, where the main goal is to determine the best model parameters. During training the purpose is to minimize the values of this function.

$$Loss = \frac{\sum (y_{true} - y_{pred})^2}{n} \quad (1)$$

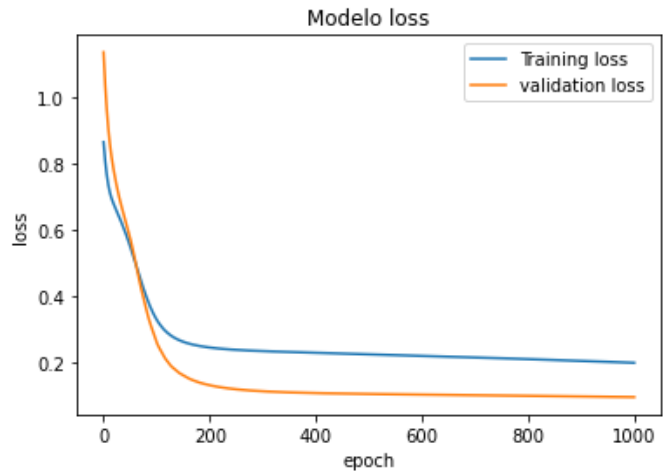


Fig. 2 Loss function for the model

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