ECG signal of a person suffering from AF, the noise has clearly reduced.

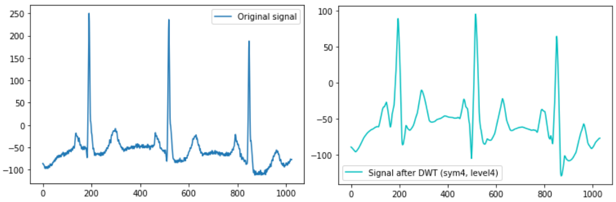


Figure 4: The ECG signal of a person suffering from AF and the same signal after applying DWT using Sym4 wavelet with level 4.

After extracting the approximation coefficient from the level 4 using the DWT, we use them to calculate the Shannon entropy (Equation (4)), which is a measure that helps to quantify the amount of information in the signal.

$$E(S) = -\sum_{i=0}^{n} p_i \log_2(p_i) \tag{4}$$

To train the deep learning model, we decided to use the obtained information resulting from the level 4 of the DWT applied to the signal, in addition of other statistical features that we calculate from each lead of the ECG, like the mean, the median, the variance, the standard deviation and the Shannon entropy. All the 12 leads of the 6877 electrocardiograms are used, so we have 82524 signals as input of the model.

## 2.4 Processing and Model Architecture

To classify the signals extracted from electrocardiograms, we decided to use the deep learning model ResNet34 [4]. The resulting coefficients of the Multi-Scale Discrete Wavelet Transform and the calculated statistical measures are the input of the data model.

ResNet34 is based on the residual neural network ResNet [4], which is an artificial neural network (ANN) that contains multiple residual blocks linked with shortcut connections forming a residual network. As we can see in Figure 5, the model consists of a first convolution layer with a 7x7 convolution followed by 4 convolution layers blocks that incorporate 34 parameter layers with a 3x3 convolution. The conv layers in-side the same block has the same dimensions. The input of each layer has an additional connection to the output of the next layer, using the technique of skip connections or shortcut connections, which allows to avoid the vanishing gradient problem.

The first block is composed of 6 convolution layers with an output size of 56x56. The second block have 6 layers with an output size of 28x28. The third block have 12 layers with an output size of 14x14. The fourth block have 6 layers with an output size of 7x7. Then we do an average and a max polling followed by a dense layer, at the out-put, we have the class of the disease predicted by the model. The data cleaning, pre-processing, and the model development were

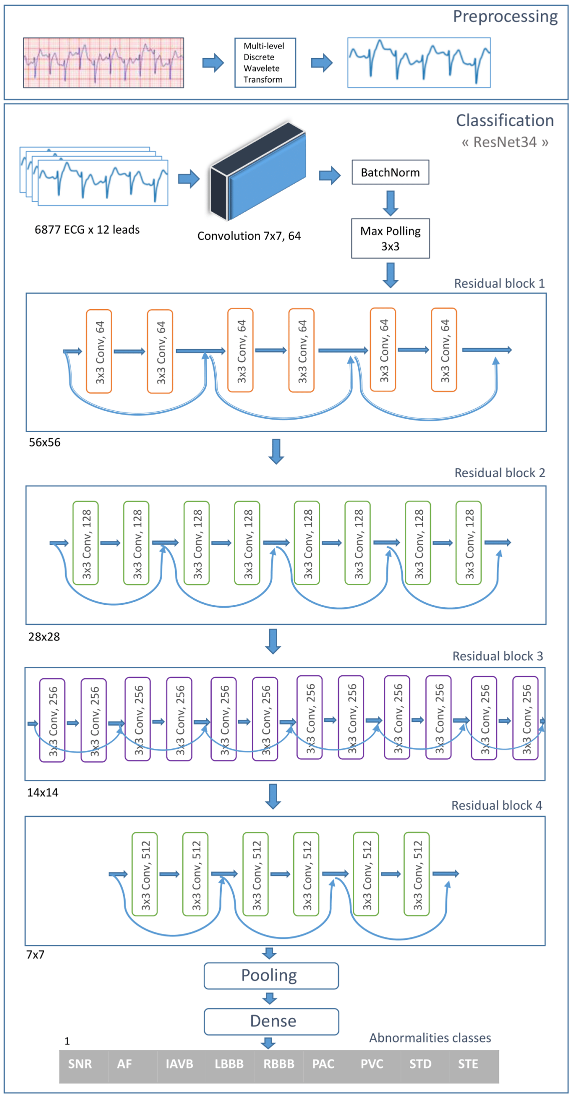


Figure 5: Preprocessing and Model training architecture.

done using Python language and the library Pytorch. For the training, we used a Dell Latitude E5470, Intel Core i5-6300 vPro, CPU 2.50 GHz 16 Go RAM.

# 3 Results and Discussion

## 3.1 General Metrics

After using sym4 and db4 wavelets in the multi-level discrete wavelet transform, the proposed deep learning model based on ResNet34 shows an AUC of 0.98, a high accuracy of 0.97, and a F1 scores of 0.86 and 0.84 for db4 and sym4 wavelets.

Table 1: Metrics results using wavelets 'Db4' and 'Sym4'.

| Wavelet | AUC | Accuracy | F1-Score |
|---|---|---|---|
| Db4 | 0.98 | 0.971 | 0.86 |
| Sym4 | 0.98 | 0.97 | 0.848 |

Table 2: AUC Metric results for the 9 classes using wavelets 'Db4' and 'Sym4'.

| Wavelet | SNR | AF | LAVB | LBBB | RBBB | PAC | PVC | STD | STE |
|---|---|---|---|---|---|---|---|---|---|
| Db4 | 0.972 | 0.988 | 0.993 | 0.998 | 0.993 | 0.962 | 0.983 | 0.972 | 0.962 |
| Sym4 | 0.98 | 0.987 | 0.99 | 0.998 | 0.992 | 0.956 | 0.978 | 0.974 | 0.966 |

Table 3: Accuracy Metric results for the 9 classes using wavelets 'Db4' and 'Sym4'.

| Wavelet | SNR | AF | LAVB | LBBB | RBBB | PAC | PVC | STD | STE |
|---|---|---|---|---|---|---|---|---|---|
| Db4 | 0.952 | 0.974 | 0.983 | 0.994 | 0.964 | 0.949 | 0.975 | 0.959 | 0.99 |
| Sym4 | 0.949 | 0.971 | 0.975 | 0.99 | 0.974 | 0.943 | 0.977 | 0.964 | 0.987 |

Table 4: F1-Score Metric results for the 9 classes using wavelets 'Db4' and 'Sym4'.

| Wavelet | SNR | AF | LAVB | LBBB | RBBB | PAC | PVC | STD | STE |
|---|---|---|---|---|---|---|---|---|---|
| Db4 | 0.824 | 0.929 | 0.92 | 0.92 | 0.934 | 0.711 | 0.855 | 0.821 | 0.829 |
| Sym4 | 0.821 | 0.921 | 0.877 | 0.877 | 0.952 | 0.683 | 0.862 | 0.847 | 0.78 |

## 3.2 Detailed Results

### 3.2.1 AUC

The Area Under Curve (AUC) represents the degree of separability. It gives the probability that the model classifies a random positive example on top of a random negative example. A higher AUC means the model distinguish between patients with CDV and no CDV.

### 3.2.2 Accuracy

Accuracy (5) represents the ratio of the number of the correct predictions to the total number of dataset samples.

$$\text{Accuracy} = \frac{\text{Nr of correct predictions}}{\text{Total nr of predictions made}} = \frac{\text{TP+TN}}{\text{Total samples}} \quad (5)$$

### 3.2.3 F1-Score

F1 score (6) balances between precision and recall. It gives us how many examples were predicted correctly and shows the robustness of the model by verifying that is not missing a significant number of instances.

$$\text{F1 score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

### 3.2.4 Confusion matrix

The confusion matrix is a way to summarize the performance of the classification model. It calculates precision, sensitivity, specificity and other metrics from values: true positives (TP), true negatives (TN), false positives (FP), false negatives (FN).

In the Figure 6, on the left, we can see that our model predicted 98.9% of the TP and 90.7% of the TN, which means that 98.9% of people suffering from Atrial Fibrillation disease were predicted correctly, and 90.7% of people who does not suffer from AF were also predicted correctly.

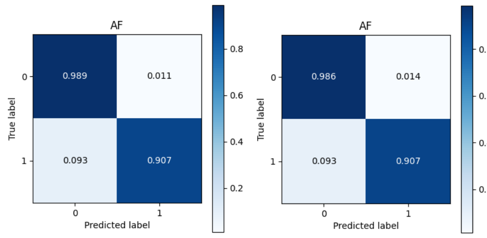


Figure 6: Confusion Matrix of Atrial fibrillation (AF) disease prediction after using Dwt with Db4 wavelet and Sym4 wavelet.

## 3.3 Discussion

In the last 5 years, many researchers proposed different deep learning model and approaches to classify ECG signals. In this paper [8], the authors propose a hybrid system combining Long Short-Term Memory (LSTM) and Convolution Neural Networks (CNN) model to classify 4 abnormalities right bundle branch block (RBBB), premature ventricular contraction (PVC), atrial premature beats (APB) and left bundle branch block (LBBB), using a database of 48 ECG recording, they got an accuracy of 98.1%. In another study [6], the authors used SVM algorithm and DWT to classify the same 4 abnormalities, the results gave 97.3% accuracy. In this work [10], authors used Rhythm Net to classify one abnormality atrial fibrillation (AF), they got an accuracy of 82%.

Few works have used DWT and all the 12 leads of the electrocardiogram to do a multi-classification with large number of abnormalities. In our study, we did the classification of 8 cardiovascular diseases using all the 12 leads. The dataset used is one of the largest databases available in the medical field, containing 6877 ECG records with 12 leads, which means 82524 signals were pre-processed. We also used statistical measures calculated from the signals and the coefficients extracted from the Multi-scale Discrete Wavelet Transform using the Daubechies wavelet 'Db4' and the Symlet wavelet Sym4, as input of the deep learning model, instead of an image of the signal or ECG raw data. The classification gave us high scores, 97.1% accuracy and 86% F1-Score using the Db1 wavelet and 97% accuracy and 84.48% F1-Score using the Sym4 wavelet.

## 4 Conclusion

In our paper, we proposed a 12 lead ECG signals classification for 8 different types of cardiovascular diseases, using the coefficients extracted for the application of the multi-scale discrete wavelet transform and some statistical measures calculated form the signals. After trying different wavelet families, we choose 'Db4' wavelet from the Daubechies family and 'Sym4' wavelet of the Symlet family for the DWT preprocessing. The results of the multi-classification of our approach using all 12 leads of the electrocardiograms, gave us high accuracy of 97.1%. We compared our work to existing papers, which most of them use Image classification while we used multilevel DWT and statistical features extracted from the ECG signal, to train the deep learning model. For the future, we will work on the optimization of the model, and try to improve the results by using additional data from other ECG datasets, and we will work on integrating the solution into a software with a graphical interface that can be used in the health sector.

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