Detection of Art erial Hypertension Through Electrocardiograms

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Abstract

Comorbidities' awareness is relevant to evaluate patients' conditions. However, very often, the main source of such information is patient self-report, which lacks reliability. Arterial Hypertension (AH) is a very relevant comorbidity that may change prognosis for several diseases. Recent studies use electrocardiogram (ECG) to diagnose and even identify relevant patient information, such as gender and age. There is also evidence that it is possible to extract patient comorbidities using the raw ECG signal. Our goal in this work is to identify AH using the 12 lead ECG signal. We use a deep neural network model tailored for learning latent features from ECG signal raw data (i.e., end-to-end approach). Our model achieved 0.89 sensibility (Recall), 0.61 positive predictive value (Precision), with an overall F1-score of 0.72. These results are significant in practice, in particular the high sensibility, considering the low prevalence of AH on patients. Despite its relatively low precision, its results are better than those associated with patient self-report, making it a potentially useful resource for physicians, mainly in telehealth practice.

1. Introduction

The electrocardiogram (ECG) is the most commonly used exam for the diagnosis of cardiovascular diseases [1], thus being an essential tool when it comes to health care, since cardiovascular diseases are the leading cause of death worldwide [2,3]. The use of computerized interpretation of the electrocardiogram (CIE) is already common, facilitating health care decision-making and reducing costs [4, 5]. However, there are limitations when it comes to the diagnostic accuracy compared to new models [6–8] and to detect new variables from the raw signal [9].

One task that is not well explored is the identification of patient information that is not commonly extracted from the ECG, such as the age and gender of the patient [10], comorbidities and even physical conditions of the patient. Commonly most of the comorbidities are self-reported by the patient, e.g., smoking, Chagas disease and hypertension. More information that can verify that self-reported comorbidities can give more information to the cardiologist during the evaluation, affect the outcome of the diagnosis, and even change the way the cardiologist treats the patient. This additional information gives more power to the expert when giving the ECG diagnosis.For that reason, it is important that there be an improvement in the automatic interpretation of ECGs, to offer even more effective treatments for the patients.

One solution is to apply recent machine learning techniques to identify automatically this additional information [11]. These techniques can identify patterns in the electrocardiograph signal that may be related to comorbidities. Recent Deep Neural Network (DNN) architectures have been applied to identification of cardiovascular diagnoses [6] and even to identify age and gender of the patient [9, 10]. These architectures are designed to identify latent patterns in the ECG, even surpassing doctors' accuracy [10].

In this paper, we try to identify Arterial Hypertension (AH) using the 12 lead ECG signal and the self-reported medications related to the presence of AH. As a result, we propose a model capable to identify AH condition with more than 0.6 area under a Receiver Operating Characteristic (ROC) Curve (AUC) and 0.85% of sensibility in our analyzed population.

2. Related Works

When it comes to Deep Learning (DL), there's a difference from traditional Machine Learning (ML). This can be seen in how representations are learned from the raw data, named in literature as "end-to-end" classification [12]. This allows computational models that are composed of multiple processing layers based on neural networks to learn representations of data with multiple levels of abstraction [13, 14]. Hence, Deep Learning has made advances in solving problems that persisted despite attempts by the artificial intelligence community for many years [13].

As a result, Deep Learning has a wide application in the medical field and, among its methods, the most used is Convolutional Neural Networks (CNNs) [15]. How-

Comorbidities	n	%
Hypertension	858866	37%
Chagas disease	58077	3%
Obesity	132297	6%
Diabetes	173254	7%
Smoking	150266	6%
Previous myocardial infarction	21685	1%
Dyslipidemia	93259	5%
Chronic kidney disease	12424	$< 1\%$
COPD	17173	1%

Table 1. Distribution of comorbidities found in our database. COPD is the acronym of Chronic Obstructive Pulmonary Disease.

ever, there are still many challenges in making full use of biomedical data, given its complexity [14].

Still, there are several works that face the challenge and use Artificial Intelligence (AI) for different purposes in the health field. When it comes to works that apply AI to ECG-related data, there are those that focus on diagnosis of cardiovascular diseases and those that use the ECG as a way to patient diagnostics [6, 10, 16].

Although there are studies that focus on recognizing comorbidities or similar conditions [17, 18], there are no other studies that predicted AH using the raw ECG signal, to the best of the authors' knowledge.

3. Dataset

The model was created using a dataset [19] containing over 2.4 million records from more than 1.5 million patients. This dataset was collected in partnership with Telehealth Network of Minas Gerais (TNMG) and corresponds to patients from 811 municipalities in the state of Minas Gerais, Brazil. This dataset has information from patients who self-reported that they have AH and information if the patient uses medications to control this same comorbidity. This dataset was collected between 2010 and 2016. The average age of patients is 51.6, with a standard deviation of 17.6 years, 40.2% of the base is made up of men. The mean mortality is 3.34% with an average return time of patients of 3.7 years. We describe in the table 1 the prevalence of comorbidities of these patients.

For the development of this project we used the following information: Tracings (ECG signals); self reported clinical data of the patient; and registration data, e.g., age and gender.

4. Method

The arrhythmia detection in ECG is a sequence classification task with the input being the ECG signal X and output the probability of the entry X is contained in the researched classes. We try to optimize the binary cross entropy function, depicted in the Equation 1.

$$L(X, y) = \sum_{i=1}^{N} -w_i * (y_i * log(x_i) + (1 - y_i) * log(1 - x_i)) \tag{1}$$

Where, w_i is the weight, x_i is the model output after activation by the sigmoid function and y_i is the target.

Our goal in this work is to present a solution for the automatic diagnosis detection of AH. To build this model, we implemented an end-to-end classifier using the raw ECG signal as input. Our approach consists of a deep neural network (DNN) model, with the architecture of a recurrent residual network. With the usage of DNN we can extract information from our large dataset to better learn latent features of the ECG that are important to discover the desirable patient condition.

Our solution consists in the classification models based on the residual networks (ResNet's) [6, 20, 21]. The Figure 1 depict the architecture of a 1d-ResNet implementation for ECG-signals.

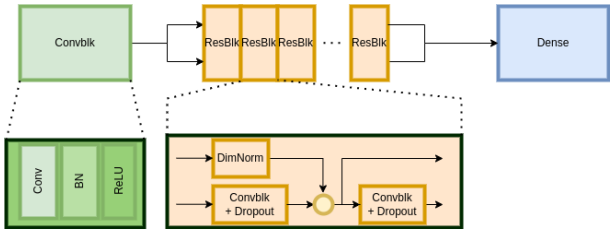

Figure 1. The 1d-ResNet architecture, divided into 3 main blocks: (1) ConvBlk (in green); (2) ResBlks (in yellow); (3) Dense (in Blue). The model was based on an implementation presented in the work [6].

We can divide our architecture into three steps, described as:

- Initially, the input data is applied into a Convolutional block (ConvBlk). This first block is composed of a 1D convolution layer, a batch normalization (BN), and finally, Rectified Linear Unit (ReLU) activation function.
- The result of the first step is fed into the residual blocks (ResBlk). The ResBlk is an implementation of skip connections, which allow the network to bypass some layer to smooth loss learning. This block is compose of the same structures described in the first step, and a dropout layer, which consists in disabling some nodes in the network to prevent model overfitting [22]. There are an dimension normalization (DimNorm) with two additional layers, MaxPooling and 1x1Conv, to normalize the dimensionality of neurons fed into the skip connection.
- In the last step (Dense), the output of the last ResBlk is fed into a fully connected layer (Dense) and with a sigmoid

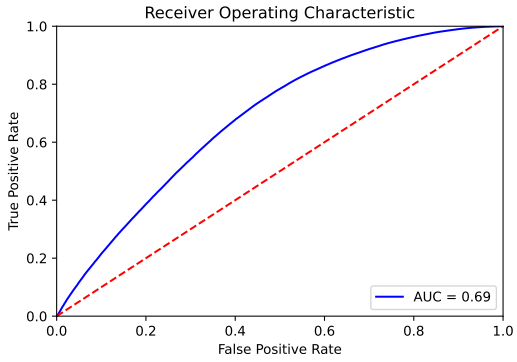

Figure 2. Roc curve of our model performance.

activation function to perform the classification of the desired class, AH.

The model was trained for a maximum of 70 epochs, using approximately 2.4 million ECG's, with the proportions between training, validation and test set being 8:1:1, respectively. To maximize our method performance, we optimize our model hyperparameters through a Random Search technique [23]. The optimization was applied in the following values:

- The probability 'p' of a node being disabled in the newtork in each epoch, the dropout rate [22], and we tested the values of 0.6, 0.7 and 0.8 for p.
- We varied the starting learning rate between 0.001 to 0.1.
- the number of residual layer blocks from 2 to 16

The best configuration found by our search is: dropout rate of 0.6, starting learning rate of 0.001 and 4 residual blocks.

In order to evaluate our model performance, we choose to use five commonly used different metrics: Sensibility, Positive Predictive Value (PPV), Area Under a receiver operating characteristic Curve (AUC), Negative Predictive Value and the F1-score.

One of the most important metric is the F1-score, which is the harmonic mean of sensibility and PPV. This metric is a tradeoff between both sensibility and PPV metrics, giving a balance value, ideal to measure unbalanced classes, as in our scenario.

5. Results

In Table 2, we summarize our model performance for all metrics used in this work. In general, our model achieved 0.887 sensibility, which is a good result, based on the unbalanced prevalence of AH in our dataset, presented in the Table 1.

The overall result is presented in the column F1-score, with a result of 0.72, is also a good result. It is also possible to note that the older the person, the better the detection

	SEN	PPV	AUC	NPV	F1
General	0.887	0.606	0.686	0.790	0.720
Males	0.886	0.535	0.688	0.797	0.667
Females	0.886	0.600	0.688	0.797	0.715
Age (20-)	0.885	0.595	0.699	0.806	0.711
Age (21 - 30)	0.890	0.599	0.691	0.803	0.716
Age (31 - 40)	0.887	0.601	0.688	0.795	0.717
Age (41 - 50)	0.888	0.603	0.688	0.795	0.719
Age (51 - 60)	0.885	0.598	0.684	0.791	0.714
Age (61 - 70)	0.889	0.603	0.687	0.796	0.718
Age (71 - 80)	0.891	0.607	0.697	0.806	0.722
Age (81+)	0.876	0.626	0.691	0.776	0.730

Table 2. Automatic diagnosis detection of arterial hypertension results segmented

of the diagnosis. Furthermore, the model performs slight better for females, which is expected once our dataset has more females than males patients.

6. Conclusions and future works

In this work, we propose and evaluate a method specialized to detect Atrial Hypertension (AH) using the ECG-signal in an end-to-end classifiers approach. Our method was optimized to this task and achieve great results both for F1-score and sensibility metrics. Methods for automated classification of AH for healthcare give to the doctor an additional tool to perform a better diagnose. This model can be applied in real contexts, specially for cardiology, where the AH condition may alter the ECG diagnosis. As far as the author's known, this is the first work that proposes a method to detect AH condition using the raw ECG data as input.

Several other comorbidities are also important to improve physician interpretation of the ECG signal. As future work, we intend to enhance our model prediction, including more patient comorbidities for prediction. We also intend to improve our results to achieve better PPV values, adapting different DNN architectures, e.g., transformers [20], which has been vastly used in recent works achieving outstanding results [24, 25].

There are some differences in our method results from the previous paper's abstract. These differences are due to minor improvements on our dataset train, validation and test split. With this new split, the model was able to train betters weights and also generate a more stable results for different ages and gender of our dataset. However, this new approach did not impact negatively the results, only improve then.

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