

# Detection of Arterial 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].

Although there are studies that focus on recognizing comorbidities or similar conditions [16, 17], 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 [18] containing over 2.4 million records from more than 1.5 million patients. This dataset was collected in partnership with the 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 whether 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.

In this work, 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  $X$  being contained in

the researched classes. We try to optimize the binary cross entropy function, defined by Equation 1.

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

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, 19, 20]. The Figure 1 depict the architecture of a 1d-ResNet implementation for ECG-signals.

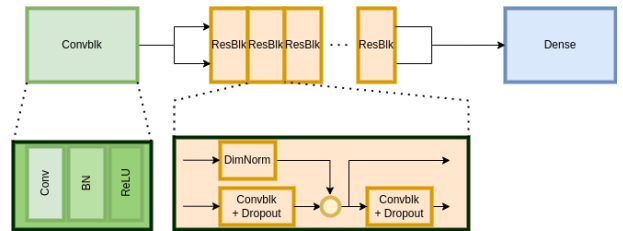


Figure 1. The 1d-ResNet architecture, divided into 3 main blocks: (1) ConvBlk (in green); (2) ResBlks (in yellow); (3) Dense (in Blue). The model was based on an implementation presented in the work [6].

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

- Initially, the input data is given to a Convolutional block (ConvBlk). This first block is composed of an 1D convolution layer, a batch normalization (BN), and, finally, a 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 composed 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 [21]. There is a dimension normalization (DimNorm) with two additional layers, Max-Pooling 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

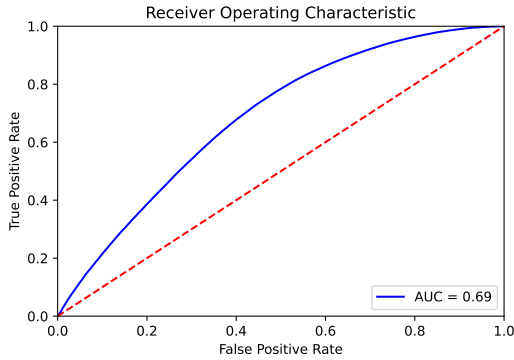


Figure 2. Roc curve of our model performance.

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 ratios 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 [22]. The optimization was applied as follows:

- The probability ‘p’ of a node being disabled in the network in each epoch, the dropout rate [21], varied among 0.6, 0.7, and 0.8.
- We varied the starting learning rate from 0.001 to 0.1.
- The number of residual layer blocks varied from 2 to 16.

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

In order to evaluate our model performance, we chose 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. F1-score, which is the harmonic mean of sensibility and PPV, is an important metric for the analysis, since it is a tradeoff between both sensibility and PPV metrics, giving a balanced value, ideal to measure unbalanced classes, as in our scenario.

## 5. Results

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

The overall result is presented in the column F1-score, namely 0.72, is a good one. It is also possible to note that the older the person, the better the detection of the diagnosis. Furthermore, the model performs slightly better for

	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

females, which is expected, since our dataset has more female than male patients.

## 6. Conclusions and future works

In this work, we propose and evaluate a specialized method to detect Atrial Hypertension (AH) using the ECG-signal in an end-to-end classifier approach. Our method was optimized to this task and achieve good results for both F1-score and sensibility metrics. Methods for automated classification of AH provide, to the doctor, an additional tool to perform a better diagnose. This model may be applied in real contexts, specially for cardiology, where the AH condition may affect 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 comorbidities for prediction. We also intend to improve our results to improve the PPV values, adapting different DNN architectures, e.g., transformers [19], which have been vastly used in recent works and are achieving outstanding results [23, 24].

There are some differences in our method results from the original abstract. These differences are due to minor improvements in our dataset train, validation and test split. This new partition strategy allowed our model to learn better weights and also to generate more stable results for different ages and gender of our dataset. Moreover, it is worth noting that this new approach did not impact negatively the performance, only improved it.

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