AN APPROACH TO COMPUTER-AIDED DIAGNOSIS OF HEART DISORDERS USING WAVELETS AND DEEP LEARNING APPLIED TO ELECTROCARDIOGRAMS (EKGS)

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DOI: 10.54751/revistafoco.v16n9-164
Recebido em: 21 de Agosto de 2023
Aceito em: 19 de Setembro de 2023

ABSTRACT

Purpose: The purpose of this study was to evaluate the potential of deep learning as a tool for computer-aided diagnosis of heart disorders based on EKG signals, using wavelet transformations to generate images. The research question was whether deep learning algorithms could accurately diagnose heart disorders and provide a valuable complement to traditional EKG views. Methods: We trained five Convolutional Neural Networks (CNNs) using EKG data obtained from the Physionet public database. The algorithms were developed using MATLAB version 2018b and the toolboxes for digital signal processing, neural networks, and wavelets. We evaluated the performance of the CNNs using accuracy, sensitivity, specificity, positive predictive value, and negative predictive value as metrics. Results: The CNNs demonstrated accuracy greater than 90%, and achieved good performance for the other evaluated parameters. We also identified that the representation of EKGs as scalograms showed potential for use as a complement to traditional EKG views. Conclusion: Our findings demonstrate that deep

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learning is a promising tool for diagnosing heart disorders based on EKG signals, and can be a valuable complement to traditional EKG views. While automated diagnoses should not replace clinical judgment, deep learning can provide additional support to healthcare professionals. Further research should explore the potential of deep learning for medical diagnosis and the use of scalograms as a complementary tool in clinical practice.

**Keywords:** Deep learning; electrocardiogram (EKG); heart disorders; wavelet transformation; computer-aided diagnosis; convolutional neural networks (CNNs).

RESUMO

Objetivo: O objetivo deste estudo foi avaliar o potencial do aprendizado profundo como uma ferramenta para o diagnóstico assistido por computador de distúrbios cardíacos com base em sinais EKG, utilizando transformações de ondas para gerar imagens. A questão da pesquisa era se os algoritmos de aprendizagem profunda poderiam diagnosticar com precisão distúrbios cardíacos e fornecer um complemento valioso para as visões tradicionais do EKG. Métodos: Treinamos cinco Redes Neurais Convolucionais (CNNs) usando dados de EKG obtidos do banco de dados público Physionet. Os algoritmos foram desenvolvidos usando o MATLAB versão 2018b e as caixas de ferramentas para processamento de sinal digital, redes neurais e wavelets. Avaliamos o desempenho das CNNs usando precisão, sensibilidade, especificidade, valor predictivo positivo e valor predictivo negativo como métricas. Resultados: As CNNs demonstraram acurácia superior a 90% e obtiveram bom desempenho para os demais parâmetros avaliados. Também identificamos que a representação de EKGs como escalogramas mostrou potencial para uso como um complemento às visões tradicionais de EKG. Conclusão: Nossas descobertas demonstram que a aprendizagem profunda é uma ferramenta promissora para diagnosticar distúrbios cardíacos com base em sinais de eletrocardiograma e pode ser um complemento valioso para as visões tradicionais de eletrocardiograma. Embora os diagnósticos automatizados não devam substituir o julgamento clínico, a aprendizagem profunda pode fornecer suporte adicional aos profissionais de saúde. Uma investigação mais aprofundada deverá explorar o potencial da aprendizagem profunda para o diagnóstico médico e a utilização de escalogramas como ferramenta complementar na prática clínica.

Palavras-chave: Aprendizagem profunda; eletrocardiograma (EKG); distúrbios cardíacos; transformação de ondas; diagnóstico assistido por computador; redes neurais convolucionais (CNNs).

RESUMEN

El propósito de este estudio fue evaluar el potencial del aprendizaje profundo como herramienta para el diagnóstico asistido por ordenador de trastornos cardíacos basado en señales electrocardiográficas, utilizando transformaciones de ondas para generar imágenes. La pregunta de investigación fue si los algoritmos de aprendizaje profundo podrían diagnosticar con precisión los trastornos cardíacos y proporcionar un complemento valioso a las vistas tradicionales del ECG. Métodos: Se entrenaron cinco redes neuronales convolucionales (CNNs) utilizando datos del ECG obtenidos de la base de datos pública Physionet. Los algoritmos se desarrollaron utilizando MATLAB versión 2018b y las cajas de herramientas para el procesamiento digital de señales, redes neuronales y wavelets. Se evaluó el desempeño de las CNNs utilizando como métricas la precisión, sensibilidad, especificidad, valor predictivo positivo y valor predictivo negativo. Resultados: Los CNNs demostraron una precisión superior al 90%, y lograron un buen desempeño para los demás parámetros evaluados. También se identificó que la representación de los ECG como escalogramas mostró potencial para
ser usados como complemento a las vistas tradicionales del ECG. Conclusión: Nuestros hallazgos demuestran que el aprendizaje profundo es una herramienta prometedora para diagnosticar trastornos cardíacos basados en las señales del ECG, y puede ser un complemento valioso para las vistas tradicionales del ECG. Si bien los diagnósticos automatizados no deben reemplazar el juicio clínico, el aprendizaje profundo puede proporcionar un apoyo adicional a los profesionales de la salud. Investigaciones posteriores deben explorar el potencial del aprendizaje profundo para el diagnóstico médico y el uso de escalogramas como herramienta complementaria en la práctica clínica.

Palabras clave: Aprendizaje profundo; electrocardiograma (ECG); trastornos cardíacos; transformación de las ondas; diagnóstico asistido por ordenador; redes neuronales convolucionales (CNN).

1. Introduction

Deep learning is a machine learning technique that implements a convolutional neural network (CNN). It operates similarly to humans by learning through experience. With images as input, the technique separates them into classes that one desires to differentiate from each other. Subsequently, the output is a trained network that can classify the images into their respective classes. The learning process of the technique involves identifying patterns that distinguish each class from the others, similar to how humans differentiate objects during learning (Lecun et al. 2015).

Over the past decade, there has been a widespread effort to utilize deep learning as a diagnostic tool, with a focus on a diverse range of physiological signals and images, including X-ray images (Becker et al. 2018; Xie et al. 2019), dermatologic lesion images (Esteva et al. 2017), histopathologic images (Rajaram et al. 2018; Nirschl et al. 2017), and electrocardiogram signals (Yildirim et al. 2018; Silva et al. 2021). These attempts have been aimed at leveraging the power of deep learning techniques to provide a more accurate and efficient diagnosis of various medical conditions.

In recent years, artificial intelligence (AI) has been utilized for electrocardiogram (EKG) analysis to diagnose various diseases. Notably, recent studies have demonstrated that AI-activated EKG has the potential to detect heart failure, pulmonary hypertension, hyperkalemia, and predict the development of atrial fibrillation and cardiac arrest. By learning an implicit representation, deep
learning models are adept at detecting subtle changes in EKGs and generating complex, nonlinear EKG data models to create algorithms (Kwon et al. 2021).

Unterhuber (2021) has reported in a recent study the first CNN enabled with deep learning for identifying patients with HFpEF (heart failure with preserved ejection fraction). The diagnostic algorithm includes measuring NT-proBNP (N-terminal prohormone of brain natriuretic peptide) among patients at risk for HFpEF. Through analyzing 12-lead EKGs, the model demonstrated that AI algorithms can recognize specific electrocardiographic characteristics indicative of HFpEF (Unterhuber et al. 2021). Similarly, Liu and Zhang (2021) proposed a CNN designed for EKG-based cardiac arrhythmia diagnosis using attentional convolutional neural networks to automatically extract distinctive information from raw EKG data.

In the medical field, accurately diagnosing heart disorders based on electrocardiogram (EKG) signals can be a challenging task, particularly for general practitioners. To address this issue, we propose a novel approach that utilizes deep learning as a diagnostic tool for detecting heart disorders through the analysis of EKGs.

Our approach is aimed at addressing the identified need for a proper methodology for applying machine learning techniques to electrocardiogram analysis. This need was highlighted by Friedrich et al. (2021) in their systematic review of the applications of artificial intelligence and machine learning in cardiovascular medicine. Our work aims to contribute to the field by providing a clear and effective approach to utilizing machine learning for EKG analysis.

We conducted an experiment utilizing deep learning by training five convolutional neural networks (CNN) with scalograms, which are representations of time-series signals generated through digital signal processing using wavelets of electrocardiograms (EKGs) as input. Figure 1 shows an example of an EKG and its corresponding scalogram.

Our study aimed to achieve the following objectives: CNN 1 - distinguish between "altered" and "non-altered" EKGs; CNN 2 - differentiate between EKG fragments containing arrhythmia and those without arrhythmia; CNN 3 - evaluate whether a CNN can differentiate between Atrial fibrillation and other arrhythmias;
CNN 4 - assess whether a CNN can classify certain arrhythmias; and CNN 5 - investigate whether a CNN can distinguish between atrial fibrillation and normal sinus rhythm.

Based on our hypothesis that a convolutional neural network (CNN) can achieve comparable accuracy to that of a specialist in identifying normal EKG variants, we aimed to develop a neural network system with the capability to analyze and detect abnormalities in electrocardiographic examinations.

2. Methods

In this study, we consider electrocardiograms (EKGs) as digital signals, which are numerical representations of the original analog signals sampled at a predefined frequency (Fs).

The overall process we designed to train our convolutional neural networks (CNNs) involves several steps. Firstly, we obtained digital EKGs from reliable databases and categorized them. Next, we extracted 15-second segments of EKGs and transformed them into scalograms. Subsequently, we established the goals of the CNNs, divided the data into training and testing sets per CNN, and trained five different CNNs. Finally, we evaluated the performance of the trained models in terms of accuracy, sensitivity, specificity, positive predictive value, and negative predictive value.

For the training phase, we utilized MATLAB R2018b software with the digital processing, wavelets, and neural networks toolboxes on a system comprising an NVIDIA GTX 1070 GPU and an I7 CPU running at 2.9 GHz. To optimize the CNNs' performance, we implemented transfer learning, using a pre-trained AlexNet (Krizhevsky et al. 2017) network architecture to extract important features before training with the Physionet® images. CNNs are neural networks well-suited to process image inputs, and they use a mathematical operation called linear convolution, as explained by Goodfellow (Goodfellow et al. 2016). AlexNet, as described by Krizhevsky (Krizhevsky et al. 2017), is a CNN pre-trained on a vast dataset of 1.2 million high-resolution images with 1,000 classes. Our process involves several steps, which we will detail below.
2.1 Step 1: Obtaining Digital EKGs from Reliable Databases

We retrieved the EKG data from the Physionet database – a “repository of freely available medical research data, managed by the Massachusetts Institute of Technology (MIT) Laboratory for Computational Physiology” (PhysioNet 2021).

To extract the EKGs and their corresponding information, we developed an algorithm utilizing the WFDB (WaveForm DataBase) Toolbox for MATLAB (Silva et al., 2021; Silva and Moody, 2014) also available on the Physionet platform. We used four databases for this study: MIT-BIH Arrhythmia Database (mitdb) (Moody and Mark, 2001; Goldberger et al., 2000), Long-Term AF Database (ltafdb) (Goldberger et al., 2000), MIT-BIH Supraventricular Arrhythmia Database (svdb) (Goldberger et al., 2000), and MIT-BIH Normal Sinus Rhythm Database (nsrdb) (Goldberger et al., 2000). Some of these databases had over 24 hours of recordings. The obtained EKG data for each database is presented in Table 1.

We extracted the following data from each file: EKG signals, sampling frequency, annotations, annotation types, comments, RR annotations, and RR intervals. Annotations and their types provide information about the characteristics of a beat (a single PQRST complex) or of a given chunk of EKG. By the end of this step, we had one “. mat” file for each EKG in each database containing all the information necessary for the subsequent steps.

2.2 Step 2: Extracting Pieces from the Original EKGs

In this study, we worked with 15-second fragments of wide EKG signals (some of them with more than 24-hour duration). We employed two methods for extracting the fragments: (1) using annotation types and RR intervals; and (2) utilizing comments from the annotations.

It’s important to point out that each EKG chunk was obtained by one of the two mentioned extraction methods, never both. This was done to avoid potential classification errors that could arise from using fragments that belong to the same class but were extracted using different methods.

For each fragment we first checked for the occurrence of arrhythmia, here defined by “any variation bigger than 15% between contiguous RR intervals.”
within the chunk. Whenever this condition was found, we categorized the chunk as “Altered” and “Arrhythmia”. If no variation bigger than 15% occurred within the EKG fragment, we checked if the annotation of the centered sample was different than “N” or any annotation type compatible with normality. If that was the case, the chunk was categorized as “Altered” and “Non-arrhythmia”. Finally, if the centered sample was of the “N” type, we checked for the presence of any annotation type within the fragment incompatible with normal EKG - in which case the chunk would also be categorized as “Altered” and “Non-arrhythmia”.

2.2.1 Extraction using “comments”

To obtain EKG chunks for training CNNs 3 and 4, we utilized a specific extraction technique. We observed that the only database with comments on annotations indicating the beginning and end of certain rhythms was "ltafdb." Therefore, we used only this database, which includes rhythms such as atrial bigeminy, atrial fibrillation, ventricular bigeminy, normal sinus rhythm, sinus bradycardia, supraventricular tachyarrhythmia, and ventricular trigeminy. It’s worth noting that some EKGs from "ltafdb" don’t have all the mentioned rhythms.

Our algorithm identified all types of comments in the EKG and, for each comment type, identified all chunks in the EKG with that comment. It pointed out the sample number of the beginning and the end for each chunk.

Each fragment was then divided into pieces of 15 seconds duration. Unlike extraction using annotation types, this extraction didn't allow the repetition of fragments between contiguous samples due to the large size of some datasets. We chose not to limit the number of extracted fragments for this extraction, resulting in a significant number of extracted fragments.

We established a rule that the entire EKG fragment must relate to only one type of comment. This approach ensures that the CNNs will not confuse an object that could be correctly classified into two classes, potentially reducing their performance. However, chunks with two types of annotations may be used in the future to identify events such as the beginning of atrial fibrillation or the return to normal.

By the end of this extraction, we had
One folder per type of arrhythmia found in the dataset
Files ".mat" of EKG fragments classified according to comment type

2.3 Step 3: Converting the EKG Chunks to Scalograms

We generated a single scalogram image for each EKG chunk using MATLAB’s wavelet and digital signal processing toolboxes, and a Mathworks function to create each scalogram image with $227 \times 227$ pixel resolution, which is the proper configuration for the pre-trained CNN AlexNet.

2.4 Step 4: Establishing the Goals and Setting the Training and Testing Folders per CNN-to-be-Trained

We established the following objectives for each CNN: differentiating between “Altered” and “Non-altered” EKGs, distinguishing between fragments containing arrhythmia from those without; identifying Atrial fibrillation and other arrhythmias; and finally, check if a CNN is capable to classify the other arrhythmias.

For CNNs 1 and 2, we established a rule where fragments of an EKG from one patient were only used for either training or testing the CNN, but not both. This was done to prevent creating biased CNNs with overestimated results. We also randomly selected EKGs for training and testing.

However, for CNNs 3 and 4, we had to relax this rule due to the limited number of chunks available for certain rhythms. As a result, chunks of EKGs from the same patients with different arrhythmias can be used for training and testing in some cases, but the same arrhythmia from the same patient is always used for either training or testing, but never both.

2.5 Step 5: Training the CNNs

Using the folder set obtained in the step 3, we ran the algorithm to train and test the CNNs. The AlexNet, a pre-trained network with 25 layers that accepts images with $227 \times 227$ pixels resolution as input, was utilized for the task.

After each CNN training, the algorithm classified the testing images to evaluate its performance and generated a confusion matrix to show the
distribution of classifications.

2.6 Step 6: Evaluating the CNNs in Terms of Diagnostic Parameters

To evaluate the performance of the CNNs, we established five percentage parameters: accuracy, sensitivity, specificity, positive predictive value, and negative predictive value.

3. Results

The study results are presented in Tables 2-7, with Table 2 containing the performance metrics for CNNs 1, 2, 3, 4, and 5. The confusion matrices are presented in Tables 3-5 for CNNs 1-3, respectively, and Table 6 shows the traditional confusion matrix for CNN 4 to highlight the correct and incorrect classifications among the classes.

In the confusion matrix, rows represent the true cases, while columns represent the CNN classifications. For instance, row 1 from Table 6 pertains to atrial bigeminy, with a total of 51 cases. In this row, 39 indicates the number of correctly classified cases (True Positives), while 1 is the number of misclassifications as sinus bradycardia, 2 is the number of misclassifications as supraventricular tachyarrhythmia, and 11 is the number of misclassifications as ventricular bigeminy.

4. Discussion

The aim of this study was to demonstrate the potential of deep learning as a diagnostic tool for EKGs. In accordance with the recommendations of Friedrich et al. (2021) in their systematic review, we described our methods in detail and presented the obtained data. In the mentioned recommendations, regarding AI applications in cardiovascular medicine, the authors emphasized the urgent need to improve reporting of the evaluation process and increase transparency regarding data and methods.

As previously reported by Rim et al. (2020), there has been a growing interest in the use of deep learning for the analysis of EKGs. In their systematic review, they identified 47 studies that applied deep learning methods to EKGs,
some of which used publicly available databases such as PhysioNet, while others used private or hybrid datasets. Among the studies that used deep learning on publicly available datasets, CNN models were found to achieve an overall accuracy of > 83% for heart disease classification (Rim et al., 2020).

A study of note employed AI to analyze EKG signals as a rapid screening tool for COVID-19 infections. The study was based on the premise that infections cause subtle electrical changes in the heart. Impressively, this study yielded a negative predictive value of 91%, indicating that it shows promise as a screening tool, especially for asymptomatic patients (Attia et al. 2021). Another study, published in 2020, demonstrated that a deep learning model based on an ensemble neural network accurately detected heart failure with preserved ejection fraction (HFpEF) using EKG, and successfully predicted the development of HFpEF (Kwon et al. 2020).

Our findings, as presented in Table 1 and the corresponding confusion matrices, suggest that our approach for extracting, classifying, and training CNNs is effective, resulting in improved performance compared to most of the studies reviewed by Rim (Rim et al. 2020).

It is worth noting that the performance of a CNN is dependent on several factors, such as the number and quality of input images, and the accuracy of their classification. Eventual and unknown imperfect classification of databases utilized in this study by their authors could have led to lower performance parameters, which might otherwise have been better.

One important limitation of our study is the small number of fragments available for training CNN 4 for some arrhythmia types. This limitation may have contributed to the unsatisfactory results obtained with this particular CNN, and highlights the need for further investigations on techniques for obtaining larger and more diverse training datasets.

A potential methodological mistake that can be found in other studies is the use of EKG chunks of enormous sizes. In future studies, we recommend using chunks of 10-15 seconds to generate each scalogram. This is important because in real-world applications, the CNN must identify abnormalities quickly. Training CNNs with large chunks would result in longer wait times for
classifications in equipment that uses AI in an intensive care unit, for example.

When working with rhythm classifications, we recommend to ensure that the same rhythm is present throughout the entire fragment, unless the aim is to detect the beginning of an event, such as AF. This is a critical aspect of rhythm classification and must be carefully considered to ensure accurate results.

Interestingly, a potential benefit of our approach was the finding that scalogram representation of EKGs could be used in the daily practice, not only with an AI tool. Similar to how X-ray provides a different view than magnetic resonance imaging (MRI), scalograms could reveal information that is hidden in the traditional representation of the electrocardiogram (See Figure 1). This could lead to new insights and improved diagnosis of cardiac conditions. Further research is needed to explore the potential of scalograms in clinical practice.

5. Conclusion

In this study, we employed deep learning to train five convolutional neural networks to assess the potential of this technique as a tool for computer-aided diagnosis of heart disorders. Our results demonstrated that deep learning has great potential for it. We achieved accuracy values of over 90% for each CNN, indicating the high accuracy and reliability of this technique in identifying heart abnormalities.

However, it is important to acknowledge that our experiment only evaluated four specific situations, and the development of a practical diagnostic tool would require training CNNs on a vast number of EKGs representing all known heart disorders, with proper classification and sampling.

Notably, the performance of CNNs depends on the number of images and their quality (in terms of both correct classification and sampling). For this reason, we provided the training CNNs the largest number of EKG chunks we could, taking into account the hardware and software available.

We acknowledge that building reliable databases with an appropriate number of EKGs for training networks is key in the use of machine learning techniques. This is a challenging task that requires the expertise of specialists. The process involves taking EKGs from many patients, classifying each beat in
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one class, and identifying the beginning and end of each rhythm. This must be performed for each known heart disease with as many patients as possible using a consistent method. Despite the complexity of this process, it is essential to ensure that the trained networks are accurate and reliable, making this a critical step in developing diagnostic tools for heart disorders.

In conclusion, we believe that the potential of deep learning as a diagnostic tool is confirmed and that it can be used in some medical applications. Our next step is to compare the results of the five CNNs with those of human performance. We plan to compare the performance of the networks with medical students, generalist practitioners, and cardiologists, as they represent different levels of expertise. We also intend to investigate whether the networks we trained can accurately classify EKGs digitized from papers. This research can potentially lead to the development of accurate and reliable computer-aided diagnosis tools for heart disorders, thereby improving patient outcomes and reducing healthcare costs.

Acknowledgements

We thank all of those who contributed to the completion of this study. We would like to thank everyone who participated, directly or indirectly, in the development of this research, enriching our learning process. The teaching institution at the University of Brasília was essential to enable the execution of this project.

Funding statement

This paper presents independent research funded by the Universidade de Brasília (UnB) in Brasilia, Federal District.

REFERENCES


BECKER, A.; BLÜTHGEN, C.; PHI VAN V. et al. Detection of tuberculosis


PHYSIONET. About PhysioNet [Internet]. PhysioNet; [acessado em 25 de
AN APPROACH TO COMPUTER-AIDED DIAGNOSIS OF HEART DISORDERS USING WAVELETS AND DEEP LEARNING APPLIED TO ELECTROCARDIOGRAMS (EKGS)

fevereiro de 2023]. Disponível em: https://physionet.org/about/.


SILVA, I.; MOODY, B.; MOODY, G. Waveform Database Software Package (WFDB) for MATLAB and Octave (versão 0.10.0). PhysioNet, 2021. DOI: 10.13026/6zcz-e163.


ANNEXES

1. Tables

Table 1: Quantity of EKGs per database

<table>
<thead>
<tr>
<th>Database</th>
<th>Number of EKGs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ltafdb</td>
<td>109</td>
</tr>
<tr>
<td>Mitdb</td>
<td>48</td>
</tr>
<tr>
<td>Svdb</td>
<td>78</td>
</tr>
<tr>
<td>Nsrdb</td>
<td>18</td>
</tr>
</tbody>
</table>


Source: Elaborated by the authors

Table 2: Performance parameters calculated for CNNs 1, 2, 3 and 5

<table>
<thead>
<tr>
<th></th>
<th>CNN 1</th>
<th>CNN 2</th>
<th>CNN 3</th>
<th>CNN 4*</th>
<th>CNN 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>95.04%</td>
<td>95.23%</td>
<td>99.71%</td>
<td>90.83%</td>
<td>92.38%</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>99.62%</td>
<td>96.52%</td>
<td>99.94%</td>
<td>99.12%</td>
<td></td>
</tr>
<tr>
<td>Specificity</td>
<td>56.59%</td>
<td>93.10%</td>
<td>93.52%</td>
<td>88.13%</td>
<td></td>
</tr>
<tr>
<td>Positive Predictive Value</td>
<td>95.07%</td>
<td>95.84%</td>
<td>99.76%</td>
<td>84.05%</td>
<td>99.37%</td>
</tr>
<tr>
<td>Negative Predictive Value</td>
<td>94.67%</td>
<td>94.20%</td>
<td>98.33%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

CNN: Convolutional Neural Network. *Because CNN4 has five classes, the other numerical parameters were not adequate as performance metrics.

Source: Elaborated by the authors

Table 3: Confusion matrix for CNN 1

<table>
<thead>
<tr>
<th></th>
<th>Altered</th>
<th>Non-altered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>50198</td>
<td>2603</td>
</tr>
<tr>
<td>Negative</td>
<td>191</td>
<td>3394</td>
</tr>
</tbody>
</table>

Source: Elaborated by the authors

Table 4: Confusion matrix for CNN 2

<table>
<thead>
<tr>
<th></th>
<th>Arrhythmia</th>
<th>Non-arrhythmia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>60731</td>
<td>2636</td>
</tr>
<tr>
<td>Negative</td>
<td>2190</td>
<td>35591</td>
</tr>
</tbody>
</table>

Source: Elaborated by the authors

Table 5: Confusion matrix for CNN 3

<table>
<thead>
<tr>
<th></th>
<th>Atrial fibrillation</th>
<th>Other arrhythmia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>22130</td>
<td>53</td>
</tr>
<tr>
<td>Negative</td>
<td>13</td>
<td>765</td>
</tr>
</tbody>
</table>

Source: Elaborated by the authors
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Table 6: Confusion matrix for CNN 4

<table>
<thead>
<tr>
<th></th>
<th>Atrial bigeminy</th>
<th>Sinus bradichardia</th>
<th>Supraventricular tachyarrhythmia</th>
<th>Ventricular bigeminy</th>
<th>Venticular trigeminy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atrial bigeminy</td>
<td>39</td>
<td>1</td>
<td>2</td>
<td>11</td>
<td>0</td>
</tr>
<tr>
<td>Sinus bradichardia</td>
<td>0</td>
<td>676</td>
<td>0</td>
<td>47</td>
<td>9</td>
</tr>
<tr>
<td>Supraventricular tachyarrhythmia</td>
<td>0</td>
<td>0</td>
<td>21</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Ventricular bigeminy</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>Venticular trigeminy</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>2</td>
</tr>
</tbody>
</table>

Source: Elaborated by the authors

Table 7: Confusion matrix for CNN 5

<table>
<thead>
<tr>
<th></th>
<th>Atrial fibrillation</th>
<th>Normal sinus rhythm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>21950</td>
<td>4164</td>
</tr>
<tr>
<td>Negative</td>
<td>195</td>
<td>30920</td>
</tr>
</tbody>
</table>

Source: Elaborated by the authors

2. Figures

Figure 1: Example of an EKG chunk with atrial fibrillation and its scalogram

Source: Elaborated by the authors