Automated Methods for Classification and Digitization of ECG Images from CVD Patients

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Abstract

Electrocardiography (ECG) is an essential tool for understanding the electrophysiology of the heart and its electrical activity in response to cardiovascular diseases (CVD). However, a physical paper-based format is common, which poses difficulties in the presence of millions of patients' data, reducing global accessibility in cardiac assessment. We propose a simple approach to digitize physical ECGs (images or papers) and a novel deep learning to classify the CVD condition (normal or abnormal) using a convolutional neural network (CNN). Digitization simply involves removing the background and reading pixels on an image mask to identify a signal. On the other hand, the CNN includes feed-forward blocks to train on automatically extracted image features. Our team, VitalRhythms, achieved a challenge classification score (F-measure) of 0.694 during the unofficial phase and an overall 10-fold cross-validation score of 0.766. Moreover, the reconstruction score (SNR) was -18.10, with a 10-fold cross-validation SNR of -13.20, but our official phase training submissions were unsuccessful. This study paves the way towards implementing sophisticated deep learning tools for the purpose of digitizing paper-based ECG and aiding the assessment of cardiovascular diseases and, thus, simplifying cardiac care in the presence of big patient data.

1. Introduction

Cardiovascular diseases (CVDs) are the most prevalent cause of death in current times, and electrocardiography (ECG) is the main tool used in reading and understanding the electrophysiology of the heart and its electrical activity in response to such diseases [1–3]. However, physicians still largely use paper-based ECG in their investigation and subsequent diagnoses, which may be slow and subjective, particularly in the age of big data. Automating the process of diagnosis by digitizing paper-based ECG images eliminates subjectivity and streamlines the process for the diagnosis of many more patients in a much shorter time frame [4–8].

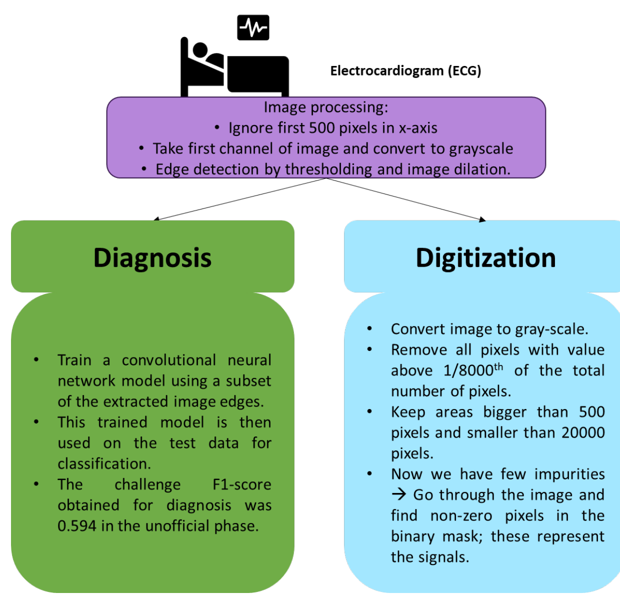

Figure 1. An overview of the methodology used for diagnosis and digitization models.

Digitization is well-known across most fields that used to be paper-based in the past; it is desirable to have all archived records as digital information as it makes it easy to process said data against possible degradation or equipment obsolescence, not to mention it makes digitalization of businesses, streamlining manual processes [9].

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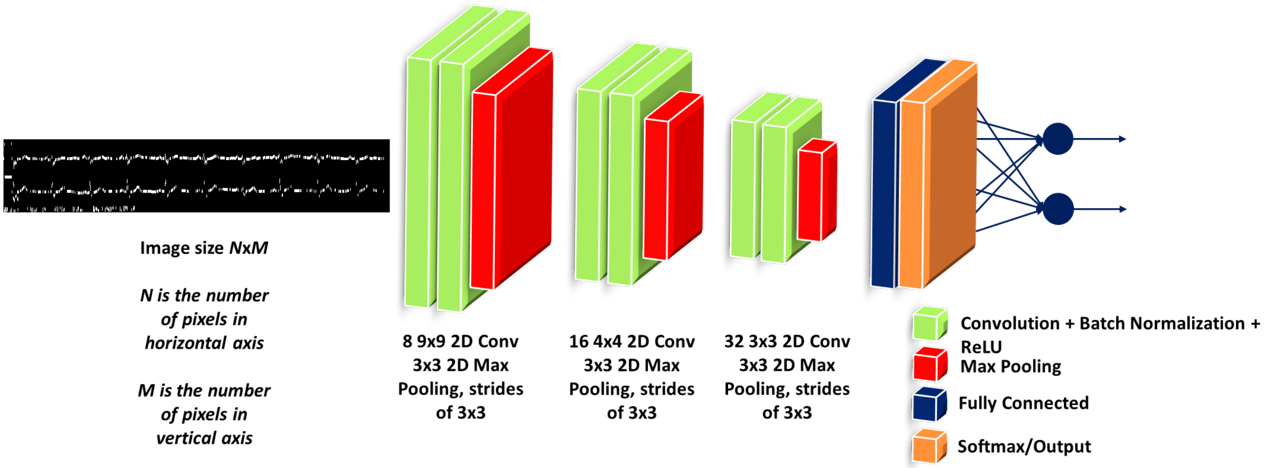

Figure 2. Convolutional neural network used.

In addition, the application of artificial intelligence, particularly deep learning, in detecting electrocardiogram (ECG) abnormalities and diagnosing heart disease has seen a boom in recent times. Many works utilize artificial intelligence to detect tachycardiac and bradycardiac arrhythmias to various degrees of success [10–15].

2. Methodology

Our methodology is split two-fold; the first half involves developing the diagnosis model, and the second is our digitization framework. While digitized signals can be used for diagnosis, we opted to develop both techniques independently since we aim to use convolutional neural networks, which are established in computer vision applications and well-suited for image classification. We remove the first 500 horizontal pixels from each image and convert its first color channel to a gray scale. Afterward, we perform edge detection by thresholding the gray-scale image, removing any component above 0.2, and then performing image dilation. Edge detection, while not ideal since it keeps text and some shadows as well as the signals, is a simple method of pre-processing that is not resource-intensive and thus easily accomplished by most machines. Now that the images are processed, we take a subset of the PTB-XL dataset provided for the challenge by Physionet [16–18] to train the neural network model shown in Figure 2 [19, 20].

Our digitization algorithm, however, does not utilize any machine learning models. We begin by converting our RGB images into gray-scale images whose pixels range in value from 0 to 255. We use MATLAB's bwareafilt function, which filters binary images by the size of objects. Firstly, we use it to obtain the bounding box of the image that crops out white space (meaning the area where pixel values were less than 255 were computed), and we remove all pixels above an optimal threshold. This threshold is computed to be 1/8000th of the size of the image. Secondly, we use it to get the final image mask; we apply it to the image to only keep areas bigger than 500 pixels and smaller than 20000 pixels, which leaves us with an image that contains at least one whole signal and generally excludes the grid and other paper contaminants like redactions or crumpling. We call this the image mask, and its pixels are binary with values equal to 1 or 0. Now that we have a cleaner representation of the ECG signals on paper in the image mask, we require a means to extract the signals into a digital format. We define the mask as rows and columns of pixels, find non-empty rows in each column, and mark them as our potential signals while removing the parts 1.5 times over the signal mean or parts equal to zero in an otherwise non-zero signal. These parts are generally caused by imperfections in the image or the algorithm misreading a row of a potential signal as part of another one. Finally, we remove potential signals that are less than 1000 samples in length, as they also seem to be artifacts, according to inspection. Generally, this whittles down our potential signals from hundreds down to less than ten, which is more reasonable considering the provided dataset includes fewer than ten ECG signals. We then apply maximal overlap discrete wavelet transform down to the 5th level with the sym4 wavelet and use the 4th and 5th levels to find QRS complexes to ensure that the signals we have left are, in fact, ECG signals. This generally leaves us with one to three remaining signals, but we keep only the first one as our final signal. Figure 3 shows two examples of how this framework digitizes an ECG signal.

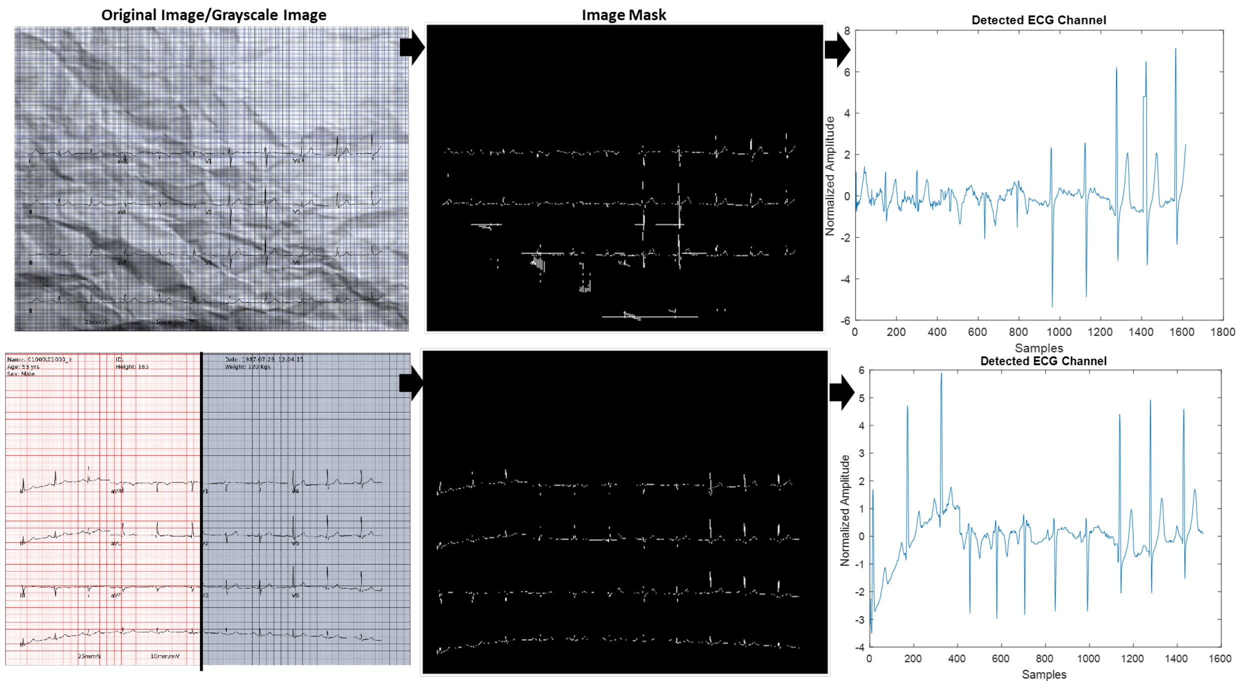

Figure 3. Digitization pipeline with a sample paper-based electroencephalogram. The figure shows two sets of images, one already black and white and another with red grids. Both images are converted to gray-scale and their eventual mask is shown. Note that the paper is crumpled in the first image, so our algorithm must adapt.

3. Results

During experimentation, we would gauge the performance of our outcome classification models based on classification F1-score, as it is this year's challenge's main metric. The challenge score is defined as follows,

$$\text{Challenge F1-Score} = \frac{2 * \text{Precision} * \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}$$

We gauge the digitization algorithm by inspecting the extracted signal and comparing it to the original image ECG signal. While suitable to observe that our algorithm actually works, it is not a quantifiable method so we also compute the signal-to-noise ratio (SNR) of the extracted signal. Our successful submission yielded a classification Challenge F1-Score of 0.594 due to the wide variety of ECG signal images, particularly with edge detection, and yielded a digitization reconstruction score (SNR) of -18.10 with a 10-fold cross-validation SNR of -13.20 in the unofficial phase. Though we did not obtain an official score due to our entries being unsuccessful, the same classification model was used as in the unofficial phase, and the EEG signal extracted was confirmed via visual inspection as seen in Figure 3.

4. Discussion

With an F1-Score of 0.594, the diagnosis model shows reasonable classification performance with simple methodology, and the digitization algorithm shows reasonable digitization SNR at -18.10. We believe combining the digitization model with the diagnosis model and training the network with sequential data (ECG signals) rather than ECG edge images may prove to be a worthy endeavor.

It would be a better alternative to keep all computed digital signals or at least select the one signal to be kept based on signal-to-noise ratios but most of our experimentation resulted in one signal being output, so the selection of the first signal was our practice to standardize the digitization process.

5. Conclusion

Cardiovascular diseases are a common cause of death globally, and detecting abnormalities in an ECG is par for the course for any cardiologist. Therefore, an automated diagnostic tool, in addition to a way to digitize paper-based ECG signals, is of the utmost importance in order to help cardiologists parse through ECG data of many more subjects than they normally could. Our diagnostic model was a convolutional neural network that yielded a classification F1-score of 0.594 and we believe that combining it with a digitization model with low signal-to-noise ratio will result in a more robust model.

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