Automated Conversion and Analysis of Printed ECG Using Random Signal Pretrained Digitizer

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Abstract

This study presents the ISIBrno-AIMT team's approach to addressing the George B. Moody PhysioNet Challenge 2024 [1][2]. The solution devised for the challenge's digitization task involves a sequential application of three neural networks: lead detection, classification, and digitization. Digitization of the leads is performed by a neural network comprising 2D convolutional layers and gated recurrent units (GRU). The pipeline initially identifies bounding boxes encompassing lead signals and their corresponding names. Subsequently, the lead names are cropped and classified, while the lead signals are extracted using the detected bounding boxes and digitized by the third network. In the final step, the lead names and signals are linked via bounding box intersection, completing the digitization process. In this task, our team achieved a score of -0.675 SNR.

The classification task to 11 different classes was addressed using a model developed for the PhysioNet/Computing in Cardiology Challenge 2021, which incorporates convolutional neural network (CNN) layers and an attention mechanism. We applied this model to digitized ECG signals obtained from the preceding digitization task. The model was fine-tuned in two stages: initially, using augmented oracle signals, and subsequently, using signals digitized by our digitization model. Our approach resulted in an F1-measure score of 0.306.

1. Introduction

Measured 12-lead ECG signal recordings have commonly been stored in printed paper form for nearly a century. Therefore, billions of ECG recordings around the world contain information about the evolution of cardiovascular diseases at different times, in different demographics, and in different parts of the world. As artificial intelligence methods are increasingly used to process and analyze ECG signals [3] [4], it is beneficial to be able to digitize the printed recordings or analyze them directly.

The difficulties of digitizing the ECG signal from printed paper form are scanning the paper, where different angles can appear. Other difficulties can be a signal resolution, horizontal shift, or signal scale. Next, to these difficulties, the signal is commonly printed in form, with a 2.5s cut of the signal from each lead and one or more full 10s recordings of the signal. However, this form is used by physicians to analyze the signal; for the signal processing methods, this brings new challenges where there are sections of the missing signals from most channels.

Nevertheless, the image processing methods that use deep learning methods have developed significantly in past years. It was shown that it is possible and beneficial to use them for ECG signal digitizing [5].

2. Method

In this paper, we present a pipeline shown in Figure 1 designed to detect and digitize signals from the commonly printed format of 12-lead electrocardiograms (ECGs) and fine-tuned and robusted PhysioNet Challenge 2021 model for the classification task.

The digitization process begins with the detection of bounding boxes for ECG signals and lead names on the printed medium, utilizing a pretrained and fine-tuned Faster R-CNN detection model [6].

The detected ECG signal bounding boxes are categorized into two groups based on signal duration: long (10-second signals) and short (2.5-second signals). These bounding boxes are then associated with the corresponding lead name bounding boxes using Euclidean distance. Any ECG signal bounding boxes that are not matched with lead name bounding boxes are placed in a separate stack for further processing.

Subsequently, the lead names are classified from images cropped using the detected lead name bounding boxes. This classification is performed using a ResNet classifier [7], which accepts an image as input and assigns it to one of the 12 lead name classes. In cases of classification duplicity, the model's probability outputs are utilized, where the most probable classification of two samples is retained as the primary one. The most probable class is subtracted

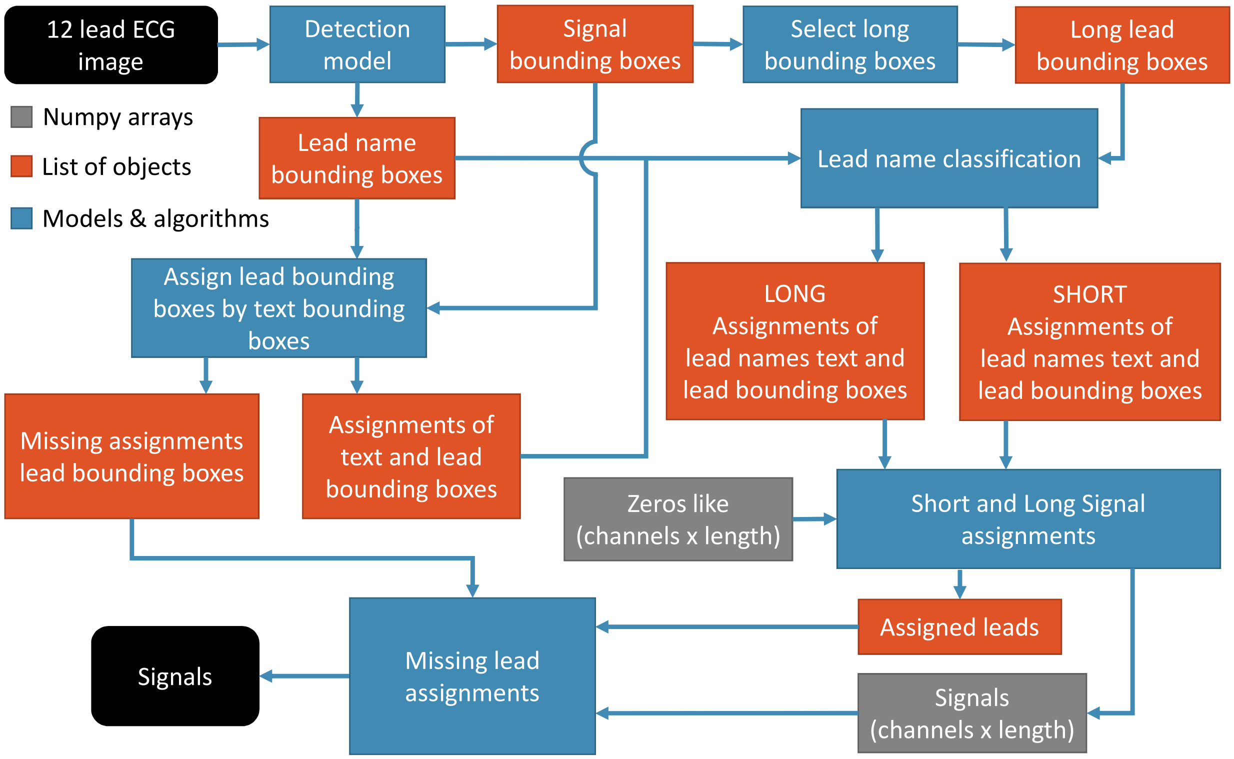

Figure 1. Pipeline for digitizing 12-lead ECG images into digital signal form. Firstly, the bounding boxes of the signals and lead names are detected. In the next step, they are assigned to each other. Finally, the signals are digitized, and signals with non-assigned leads are heuristically assigned to the final Signals array.

from the classification results of the second sample, and the new most probable class is selected as the result.

The third stage involves signal digitization, employing a convolutional neural network (CNN) model that is pretrained on generated images containing random signals and fine-tuned on cropped ECG signals from printed ECG images. The model inputs a single lead ECG image and outputs a time series with a length of the image's width. Subsequently, the output signal is resampled to the desired sampling frequency.

In the final steps, unmatched signal boxes are assigned to missing lead names according to the most common format of the printed ECG to minimize data loss. For leads containing both short and long signals, only the long signals are utilized due to their higher information content.

Following signal digitization, the estimated signals are fed into the classification model. This model is based on the winning entry from the PhysioNet Challenge 2021 [8], which consists of the convolutional layers used as an encoder followed by the attention layer. The output of the attention layer is then pooled using the maximum pooling and used as an input for the final linear layer. The model is initially pretrained on the PhysioNet Challenge 2021 dataset [3], after which the output layers are replaced with new layers suited for the current 11-class classification task. The model is then fine-tuned using the current challenge data and digitized signals.

3. Training

The training process for the digitization task involves the sequential training and fine-tuning of the models within the pipeline described in Section 2. All models are trained using artificially generated ECG signal images, formatted as printed records, derived from the PTB-XL dataset signals [9] and annotated using the PTB-XL+ dataset [10]. The image generation process follows the parameters established by the code in [11][12], which were configured to operate under fully random conditions while being enhanced to provide detailed information regarding bounding boxes.

The detection model [13] utilizes pretrained weights from the COCO dataset [14] and is subsequently fine-tuned with bounding boxes provided by the image generation algorithm.

The second model, responsible for lead classification, is trained using cropped segments from the generated images in conjunction with the bounding boxes, followed by conventional classifier training.

The digitization model is trained on randomly generated signals produced by a random walk, which are then processed using a low-pass filter (40Hz). These random signals are augmented by adding peaks that mimic QRS complexes, and the images are enhanced with various lighting effects and blurring techniques. The signals are then overlaid onto images with varying background colors and spatial grids. These images, along with the corresponding time series data, are used to train a neural network to reconstruct the original signal from the augmented image.

The classification model was pretrained using the data for the PhysioNet Challenge 2021 and the training codes for the winning model. The model was then finetuned in two stages with different output layers to the current classification task. The first stage uses the original PTB-XL signals with augmentation of randomly cutting the signals to 2.5s segments in multiple leads to simulate digitized signals from the paper form. The second stage uses the trained digitization model and trains the classification task on the digitized signals by this model to make the model more robust towards the digitization model outputs.

4. Results

A signal-to-noise ratio (SNR) score of -0.675 was obtained for the digitization task on the PhysioNet Challenge hidden data [15]. This result indicates the digitization algorithm's suboptimal performance. However, it is important to note that the SNR metric is highly sensitive to the signal's scale. Consequently, even when the ECG signal is digitized correctly, but with a different scale, the approach would achieve a low SNR metric score.

For the classification task, an F1 score of 0.306 was achieved on the PhyisoNet Challenge hidden data. The F1 score, calculated from true positive and false negative samples, is sensitive to the selection of classification thresholds. However, no threshold selection algorithm was implemented in our approach. Therefore, incorporating such an algorithm could potentially enhance the classification performance.

Table 1. Result on the digitization task

Task	Score	Rank
Digitization	-0.675	12/16
Classification	0.306	11/16

5. Discussion

The digitization task on the PhysioNet Challenge hidden data did not yield a satisfactory SNR score. This outcome could be attributed to two primary factors. First, the algorithm may inaccurately estimate the signal's scale, despite generating a signal with appropriate morphology. Such a discrepancy in scale could adversely affect the SNR metric.

Second, errors in correctly associating signal and lead name bounding boxes could result in signal misalignment. This is critical, as incorrectly matched leads could cause the SNR to be calculated between disparate leads, thereby reflecting the shortcomings of the detection and assigning algorithm rather than the digitization model.

The appropriateness of the SNR metric in this context is debatable, given its sensitivity to factors that are not necessarily critical for ECG signal analysis. Specifically, SNR is affected by variations in signal scale as well as vertical and horizontal shifts. The PhysioNet Challenge team has addressed these shifts using an alignment algorithm based on correlation and autocorrelation techniques. Nevertheless, the scale was not addressed, and involving a new metric for this task could be beneficial.

Our classification task relies on digitized signals, making the performance of the classification model contingent on the efficacy of the digitization algorithm. An alternative approach would involve using ECG images directly as input for classification, potentially improving results. However, implementing this approach would require a significant revision of our architecture.

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References

[1] Reyna MA, Deepanshi, Weigle J, Koscova Z, Elola A, Seyedi S, Campbell K, Clifford GD, Sameni R. Digitization and Classification of ECG Images: The George B.

Moody PhysioNet Challenge 2024. Computing in Cardiology 2024;51:1–4.

[2] Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, Peng CK, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. Circulation 2000;101(23):e215–e220.

[3] Reyna MA, Sadr N, Alday EAP, Gu A, Shah AJ, Robichaux C, Rad AB, Elola A, Seyedi S, Ansari S, et al. Will Two Do? Varying Dimensions in Electrocardiography: The PhysioNet/Computing in Cardiology Challenge 2021. In 2021 Computing in Cardiology (CinC), volume 48. IEEE, 2021; 1–4.

[4] Reyna MA, Sadr N, Alday EAP, Gu A, Shah AJ, Robichaux C, Rad AB, Elola A, Seyedi S, Ansari S, et al. Issues in the Automated Classification of Multilead ECGs Using Heterogeneous Labels and Populations. Physiological measurement 2022;43(8):084001.

[5] Li Y, Qu Q, Wang M, Yu L, Wang J, Shen L, He K. Deep Learning for Digitizing Highly Noisy Paper-Based ECG Records. Computers in biology and medicine 2020; 127:104077.

[6] Ren S, He K, Girshick R, Sun J. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE transactions on pattern analysis and machine intelligence 2016;39(6):1137–1149.

[7] He K, Zhang X, Ren S, Sun J. Deep Residual Learning for Image Recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition. 2016; 770–778.

[8] Nejedly P, Ivora A, Smisek R, Viscor I, Koscova Z, Jurak P, Plesinger F. Classification of ECG Using Ensemble of Residual CNNs with Attention Mechanism. In 2021 Computing in Cardiology (CinC), volume 48. IEEE, 2021; 1–4.

[9] Wagner P, Strodthoff N, Bousseljot RD, Kreiseler D, Lunze FI, Samek W, Schaeffter T. PTB-XL, a Large Publicly Available Electrocardiography Dataset. Scientific data 2020;7(1):1–15.

[10] Strodthoff N, Mehari T, Nagel C, Aston PJ, Sundar A, Graff C, Kanters JK, Haverkamp W, Dössel O, Loewe A, et al. PTB-XL+, a Comprehensive Electrocardiographic Feature Dataset. Scientific data 2023;10(1):279.

[11] Shivashankara KK, Shervedani AM, Clifford GD, Reyna MA, Sameni R, et al. ECG-Image-Kit: A Synthetic Image Generation Toolbox to Facilitate Deep Learning-based Electrocardiogram Digitization. Physiological Measurement 2024;45(5):055019.

[12] Deepanshi SK, Clifford G, Reyna M, Sameni R. ECG-Image-Kit: A Toolkit for Synthesis, Analysis, and Digitization of Electrocardiogram Images, January 2024. Online at httpsgithub comalphanumeri cslabecg image kit 2024;.

[13] Paszke A, Gross S, Massa F, Lerer A, Bradbury J, Chanan G, Killeen T, Lin Z, Gimelshein N, Antiga L, et al. Pytorch: An Imperative Style, High-Performance Deep Learning Library. Advances in neural information processing systems 2019;32.

[14] Lin TY, Maire M, Belongie S, Hays J, Perona P, Ramanan D, Dollár P, Zitnick CL. Microsoft Coco: Common Objects in Context. In Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13. Springer, 2014; 740–755.

[15] Reyna MA, Deepanshi, Weigle J, Koscova Z, Campbell K, Shivashankara KK, Saghafi S, Nikookar S, Motie-Shirazi M, Kiarashi Y, Seyedi S, Clifford GD, Sameni R. ECG-Image-Database: A Dataset of ECG Images with Real-World Imaging and Scanning Artifacts; A Foundation for Computerized ECG Image Digitization and Analysis, 2024. URL `https://arxiv.org/abs/2409.16612`.

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