Mobile app for the digitisation and deep-learning-based classification of electrocardiogram printed records

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Abstract. The interpretation of electrocardiograms (ECG) plays an important role in diagnosis and monitoring cardiovascular diseases. Nowadays, 75% of deaths related to cardiovascular diseases are in low and middle-income countries, where the access to fully experienced cardiologists is more limited. Moreover, the implementation of computer-assisted clinical decision making systems is hampered by old ECG equipment, which does not allow for exporting a digital copy of the registered trace. In these environments, the primary care centres and emergency units need new ECG interpretation techniques that enable a rapid and simple diagnosis. This could be provided by mobile phone applications, available in low-income countries, where ECG classification algorithms, based on machine learning (ML) techniques, could be embedded. In this work, we present a two-fold solution to this problem. Firstly, an user-friendly Android-based mobile app for the embedding of the algorithms and the ECG record capture. On the other hand, an algorithm for ECG digitisation and ML-based classification, considering different orientations and illuminations. Some preprocessing was required to remove the illumination defaults and rectify the image with a projective transformation for the extraction of the signal with a Python algorithm based on the HSV color scheme. Afterwards, the extracted ECG was preprocessed and introduced into a deep learning algorithm, also embedded in the mobile application framework and pre-trained on the China Physiological Challenge database, composed of 12-lead ECG recording of 6877 patients with 9 labels. The deep learning algorithm was based on a residual neural network with 3 convolutional blocks, 3 convolutional layers overlapped with a batch normalization layer and an activation layer. The proposed methodology was tested on a set of synthetic and 50 real ECGs, achieving an accuracy of 88% and root mean square error(RMSE) of 0.778. These preliminary results pave the way for improved ECG interpretation in clinical environments such as in emergency units.

Keywords: Deep learning · ECG · Android · Digitisation · Mobile app

1 Introduction

The electrocardiogram (ECG) captures the sums of myocardial action potentials in a patient's skin, providing a useful tool for assessing cardiovascular diseases (CVD) affecting the heart's electrical conduction system. The ECG is often employed for the diagnosis and monitoring of cardiovascular diseases [1]. This non-invasive test uses electrodes to record the electrical activity of the heart with an electrocardiogram machine that amplifies and filters the signal. Even though the majority of ECG machines are provided with interpretation systems, these methods are based on digital signal processing of the trace and are sometimes unreliable, reducing its applicability for automated diagnosis. Furthermore, the interpretation of these signals is still a complicated task for even the trained clinicians, which can lead to misdiagnosis and delayed treatment. As a result, high-quality assisted ECG interpretation is still an unachieved goal that may be crucial for correct clinical decisions.

Many computational solutions exists for the automatic processing of cardiac signals. Digital signal processing (DSP) has been historically used due to its ability to produce alternative data representations to ease data analysis and its adaptability to a wide variety of tasks, such as ECG delineation [2]. However, in recent times, DSP-based methods are progressively being replaced by more reliable methods as they required complex and time-consuming procedures as the extraction of key features. Nowadays, Machine Learning techniques are being adapted to ECG processing, not only for wave classification but also for ECG delineation [3,2]. The development of these ML-based processing algorithms was possible due to the availability of annotated databases of ECG recordings such as the ones available in the PhysioNet repository [4]. However, the development of these interpretation ML-based tools is hampered due to the lack of digital ECG records in many clinical centers, which prevents their implementation for the analysis of cardiac signal data. Lampreave et al. [5] addressed this limitation and proposed a method for the digitisation and classification of

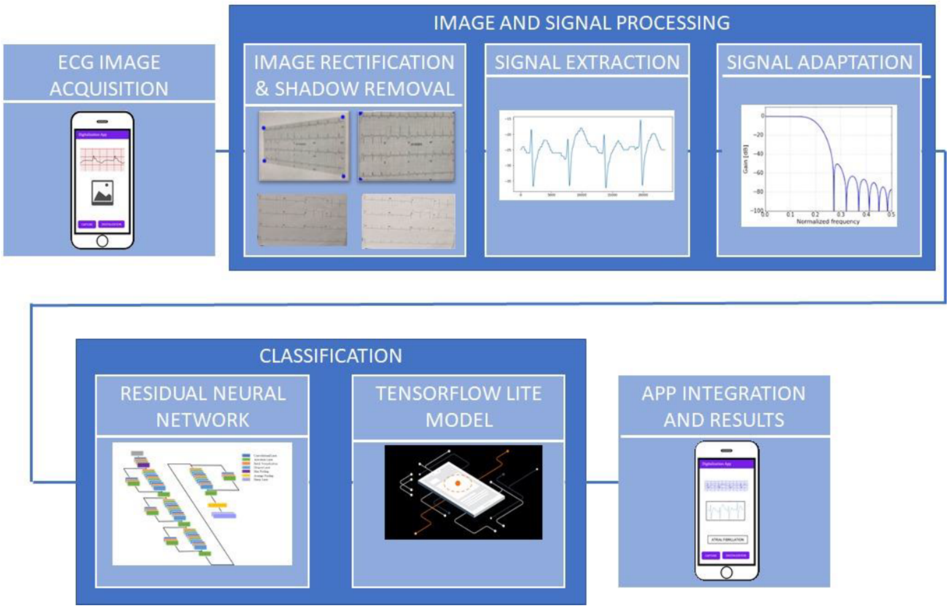

Fig. 1. Developed methodological pipeline for mobile-based electrocardiogram (ECG) digitization and classification including the following steps: ECG image acquisition, image and signal processing, classification and app integration.

ECG printing records with Augmented reality (AR) technologies based on the AR acquisition of the image and the extraction using the HSV color scheme and k-means clustering for the signal classification with a convolutional neural network. However, this technology is difficult to be made available in low-income countries, given the equipment cost, obstructing its implementation. A similar objective is shared by the wearable scientific literature (e.g., Apple Watch), which employs devices that capture ECG traces on demand to propose a diagnosis. These algorithms, however, are also difficult to apply in low-income scenarios and do not consider the use of ECG printed records.

In this paper, we propose a computational framework for the digitisation and classification of paper-based ECGs embedded inside a mobile app, which has the advantages of requiring a minimal set up (neither a VR headset nor the increased cost of a wearable) and benefiting from the robustness of state-of-the-art ML algorithms. The developed algorithm was tested on simulated ECG images built from the China Physiological Challenge database and 50 real images from the Hospital Universitario Puerta del Mar in Cádiz, Spain, acquired with a scan device or with the camera of a mobile device.

2 Methods

The proposed methodology is illustrated in Figure 1. First, the ECG printed record is captured with the mobile phone camera. Subsequently, the image is processed to perform a rectification and a shadow removal steps. Finally, the signal is extracted from the image to feed a deep learning algorithm previously trained with the signals from the China Physiological Challenge [6]. These operations are embedded in a mobile phone application, which encapsulates these operations.

In order to develop the pipeline, a synthetic database we previously developed [5] was used, where ECG gridlines were added to the signals of the China Physiological Challenge database. This database included 6877 scanned images and 100 captured images with the camera of a mobile device. Moreover, 50 real ECG from Hospital Universitatio Puerta del Mar in Cádiz, Spain, were used to test the generalization of the processing algorithms.

2.1 Image rectification and shadow removal

In order to reduce image acquisition, the image was preprocessed to facilitate the signal extraction. Firstly, in case it was needed, a shadow removal algorithm was applied, which consisted in applying a division normalization between the grayscale image and the image smoothed with a Gaussian filter. Secondly, the image was rectified to remove the background and to correct perspective distortions, projecting them into a common plane for which three different orientations were considered. This step was performed obtaining the edges of the ECG image, without the background, with the classical Canny edge detector. Subsequently, the vertices of the images were identified by calculating the minimum distance point between the limit of the record and the edge of the ECG. Once the vertices were detected, the maximum width and height was calculated to correct delimit the dimensions of the image. Finally, the rectifying transformation was performed by applying the following OpenCV[1] functions: getPerspectiveTransform() and warpPerspective().

2.2 Signal processing

After applying the rectification, the image was adapted to the signal extraction. Firstly, an algorithm to increase the brightness was applied to better identify the signal and the background when other illumination defaults were present, commonly found in images captured with the camera of a mobile device. Subsequently, the image was prepared for the extraction, which was based n the HSV colour scheme, which remaps the RGB scheme into three interdependent dimensions: hue (H), saturation (S), value (V). Then, a bilateral filter was applied to remove the noisy activations of the image. Afterwards, a binary mask was generated to isolate the pixels corresponding to the signal and a cubic interpolation was performed to complete the missing pixels. The binarization process created high-frequency artifacts that were smoothed using a bandpass filter. Finally, the y-axis iwas adapted to be centered in the median and rescaled to recover the original amplitude.

2.3 Classification

The employed classification network, loosely inspired by the work of Li et al. [7], consisted in a ResNet containing three convolutional blocks, with LeakyReLU activations and regularization strategies such as batch normalization, Spatial Dropout [8] and Gaussian noise [2] to reduce overfitting. The network was adapted to use 12 leads as inputs and output 9 categories. The network was trained using cross-entropy loss, a batch size of 100 and the Adam optimizer, with a starting learning of 0.001. Other architectures were tested including a CNN [9] and a bidirectional LSTM [10], all developed in Python with Keras[2].

The models were trained using the China Physiological database alongside the extracted signals from the same dataset, after their synthetic representation as images and digitisation (with and without post-processing, to increase variability).

2.4 Android app

The Android app,designed with Android Studio and Java language, was conceived to guide the user through the aforementioned steps in the pipeline in the user interface. For that purpose, four buttons were included: two for the access to the gallery, the camera and two buttons for the rectification/shadow removal and the digitisation/classification. The app included all the libraries required for running the algorithms. For this purpose, Python 3.8 was installed alongside OpenCV and Keras through the usage of Chaquopy[3], a plug-in that enables the execution of Python code inside Android Studio. Finally, the model's weights were also included in the app, and TensorFlow Lite[4] was employed for its usage in a mobile environment.

3 Results

The ECG rectification correctly detected the vertices in 100% of the images, including synthetic and real ECG with scanned and non-scanned images, in which the shadows removal algorithm permitted the correct delimitation of the edges. The obtained performance with different levels of ECG image orientation was also successful in 100% of the cases where the angle of declination of the image did not exceed 20 degrees.

Concerning the signal extraction, it was 100% accurate in the cases where the image was scanned. In non-scanned images, real and synthetic images, the extraction was only possible in presence of homogeneous distribution of shadows, in which the brightness increase permitted the extraction. This factor only allowed the extraction in around 50% of the cases. Moreover, the

[1] https://opencv.org/
[2] https://keras.io/
[3] https://chaquo.com/chaquopy/
[4] https://www.tensorflow.org/lite

signals were evaluated with a sample-by-sample RMSE between the original synthetic signal and the one recovered obtaining a value of 0.778.

The classification results of the digital and extracted signals showed a higher performance in the ResNet model, providing an accuracy of 88% in the adapted signal training, in contrast to the 43% of the CNN and the 59% of the bidirectional LSTM. Moreover, the signal pre-processing after digitisation benefited the performance of the network, increasing its capability to produce true positive results and improving its performance from 26% to 88%. Finally, the results of the prediction were displayed in the app showing the two arrhythmias most likely arrhythmias according to the ML-based pipeline and the probability of each.

4 Discussion and conclusions

The continuous technological advances and digitisation of ECG recordings provide new alternatives to help clinicians to make more precise diagnosis. However, the implementation of advanced ML-based tools is hindered in low-income countries, where the non-digitisation of ECG and the poor economic resources impede the advances in the diagnosis of cardiovascular diseases. Although ML-based pipelines have reduced the gap between analogical diagnostic test and digital computer methods, there are few technological approaches that requires low-cost technologies and permits its implementation in undeveloped countries. This work has presented a promising method for the extraction of ECG signals from printed ECGs for the classification of arrhythmias with a mobile app, considering a variety of alternatives to produce a robust analysis solution. It is a portable, manageable and low-cost tool that incorporates assistance systems for the diagnosis, potentially being useful in health environments with limited resources, in which other solutions such as VR headsets could be impractical. However, it requires further development to solve its limitations such as its higher dependency on a homogeneous distribution of the illumination defaults, the implementation of a more accurate function for the rectification or the lack of a more generalized solution to deal with different ECG formats. Regarding the ML classification, although many approaches in the literature outperform our classification approach, the focus of the employed network was to provide a full complete pipeline rather than optimizing towards competitive classification accuracies. Moreover, computational cost limitations posed by mobile devices prevents the usage of high-capacity networks. Future work will focus on a more exhaustive evaluation of the developed app in real clinical environment.

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