Digitization of ECG signals from cell phone images

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***Abstract*— This review paper explores the development of an innovative app designed to digitize electrocardiogram (ECG) signals from cell phone images using OpenCV, with a primary focus on rural development with Anganwadi workers. The app aims to provide a convenient and accessible tool for Anganwadi workers to capture and analyze ECG signals in real-time using their smartphones. The paper discusses the motivation behind the project, the methodology employed, and the technical challenges encountered during development. Additionally, it highlights the potential impact of such technology on improving healthcare accessibility and affordability in rural areas. The review concludes with a discussion on future directions and the integration of additional features to enhance the app's functionality and usability for Anganwadi workers.**

Keywords*— ECG signal, cell phone images, OpenCV, healthcare, real-time analysis, accessibility, affordability, resource-limited settings, future directions.

I. Introduction

Electrocardiography (ECG) is a vital diagnostic tool for monitoring heart health, but its availability in rural areas is often limited. The lack of access to ECG machines and trained personnel hinders timely diagnosis and management of cardiac conditions in these regions. To address this challenge, we propose the development of a mobile application that can digitize ECG signals from cell phone images.

The proposed app aims to empower rural health center workers with the ability to capture and digitize ECG signals using just a smartphone. By leveraging the smartphone's camera, the app will allow health workers to acquire ECG reports easily and efficiently, without the need for specialized equipment. This digitization process will enable the ECG signals to be stored, analyzed, and shared with healthcare professionals for remote diagnosis and consultation

The app's design and functionality will be tailored to meet the needs of rural health workers and the communities they serve. It will feature a user-friendly interface, intuitive controls, and real-time feedback to ensure ease of use and accuracy in signal acquisition. Additionally, the app will prioritize data privacy and security, adhering to relevant regulations and best practices.

By providing rural health center workers with a tool to digitize ECG signals, this app has the potential to significantly improve the detection and management of cardiac conditions in rural areas. It can help bridge the gap in healthcare access, empower frontline health workers, and ultimately enhance the health outcomes of rural populations.

II. Literature Review

Electrocardiography (ECG) is a fundamental tool in diagnosing cardiac conditions, but its traditional paper-based format presents challenges in terms of accessibility and analysis. In recent years, various methods utilizing advanced technologies have emerged to digitize ECG signals, aiming to improve efficiency and accuracy in signal acquisition and processing.

Hospital et al. [1] recorded ECG signals in both paper and digital formats using specialized equipment. They scanned paper reports and stored them electronically, allowing for comparative analysis and model training. Template-matching approaches were utilized to extract clean and continuous waveforms, facilitating subsequent segmentation and analysis tasks.

Another approach, outlined by Saidhan Hospital and STEMI Global [2], focused on image acquisition and preprocessing. ECG records initially in paper form were converted to digital

images using scanning or deep learning models. Preprocessing steps included extracting individual leads from multi-lead ECG images and applying binary image extraction techniques to isolate the ECG signal from background noise.
Furthermore, a study conducted at the American University of Beirut Medical Centre [3] introduced a comprehensive framework for ECG digitization, encompassing preprocessing, region of interest detection, and signal extraction stages. Preprocessing techniques were employed to filter image noise and to enhance image quality, laying the foundation for subsequent analysis steps.
Additionally, a method outlined by [4] involves scanning ECG strips printed on thermal paper, enhancing scanned images using de-skewing and noise removal techniques, and applying color-based and region-based segmentation to remove gridlines and isolate the ECG signal. The final processed ECG signal is represented by specific signal pixel per column and compressed for efficient storage and transmission.

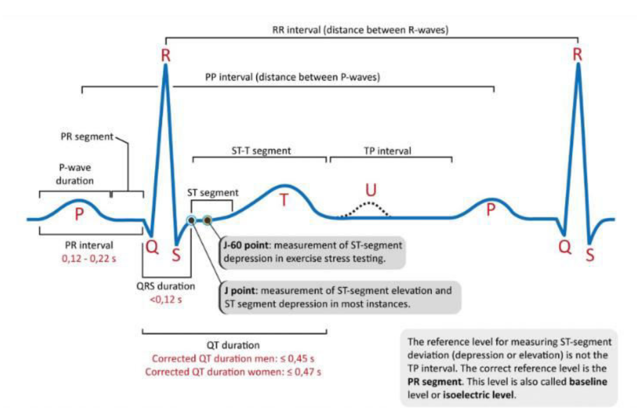

Fig .1. Representation of complete electrical activity of the heart.

Arrhythmia diagnosis studies traditionally focused on ECG signal noise filtering, waveform segmentation, and manual feature extraction. Researchers have explored several machine learning (ML) and data mining techniques for arrhythmia classification. Sahoo et al. [6] employed Discrete Wavelet Transform and Empirical Mode Distribution (EMP) for noise reduction and Support Vector Machine (SVM) for classifying five types of arrhythmias with 98.39% accuracy and 99.87% sensitivity, and a low error rate of 0.42. Osowski et al. [6] utilized higher-order statistics (HOS) and Hermite coefficients to detect QRS complexes and compared their approaches with other methods, achieving an average accuracy of 98.7%, 98.85%, and 93%. While these models are highly accurate, the manual feature extraction process made them computationally expensive. Plawiak et al. [6] used higher-order spectra for feature extraction, PCA for dimension reduction, and SVM for identifying five forms of arrhythmia with 99.28% accuracy.

A study by [5] Utilized information from clinical research conducted at the Oregon Health & Science University (OHSU) to develop and validate an algorithm for ECG digitization. They recorded routine resting 10-second 12-lead ECGs and digitized paper ECGs using scanning. The algorithm involved preprocessing, lead localization, and signal extraction, providing an open-source software code for implementation.
These studies highlight the diverse approaches and methodologies employed in digitizing ECG signals, each contributing to the advancement of ECG analysis and diagnosis. By transitioning from paper-based records to digital formats, healthcare providers can be benefited by improved accessibility, accuracy, and efficiency in managing cardiac conditions. Future research in this field may focus on enhancing automation, refining signal processing algorithms, and integrating digitized ECG data into clinical practice seamlessly.

III. IMPLEMENTATION DETAILS

1. User Interface Design:

The user interface (UI) of the application provides options for either clicking a picture of an ECG report using the device's camera or uploading an existing image of an ECG report from the gallery.

2. Image Processing Steps:

- Simple Thresholding:

  Simple thresholding is a basic method to segment an image into binary image (black and white) based on a fixed threshold value. In the context of ECG signal digitization, this technique can be used to separate the ECG signal (which typically has high intensity) from the background noise (which has lower intensity).
  Convert the image to grayscale to simplify processing. Then, set a threshold value. Pixels having intensity values greater than the threshold are set to a certain value (e.g., white), while pixels below the threshold are set to another value (e.g., black).

- Otsu's Thresholding:

  Otsu's thresholding is an automatic thresholding technique that minimizes intra-class variance to find the optimal threshold value. It assumes that the image contains two classes of pixels (foreground and background) and calculates the optimal threshold separating these classes.
  Compute the histogram of the grayscale image. Then, find the threshold value that minimizes the weighted within-class variance of the histogram. Pixels exceeding this threshold are categorized as components of the ECG signal, while pixels below are considered background.

- Non-local Means Denoising:

Non-local means denoising is a technique used to reduce noise in images by averaging similar patches. It exploits the redundancy in natural images, assuming that similar-looking patches within an image are likely to have the same signal content.
a small window (e.g., 5x5) in the image and find patches in the image that are similar to this window. Average these patches to get a denoised version of the image. This step helps improve the quality of the ECG signal by reducing noise.

- One-Lead Signal Extraction:

  In ECG signals, each lead represents a different perspective of the heart's electrical activity. For simplicity, one lead (e.g., lead II) can be selected for further processing. This step involves identifying and extracting the ECG signal from the selected lead. Loop through all the columns of the processed image and identify the location of black pixels. These black pixels represent the ECG signal. Store the positions of these black pixels along the time axis to reconstruct the ECG signal.

These steps in image processing are designed to enhance the ECG signal, reduce noise, and prepare the image for accurate extraction of the ECG signal to conduct additional analysis and digitization.

IV. System Analysis And Design

A. Flow Chart

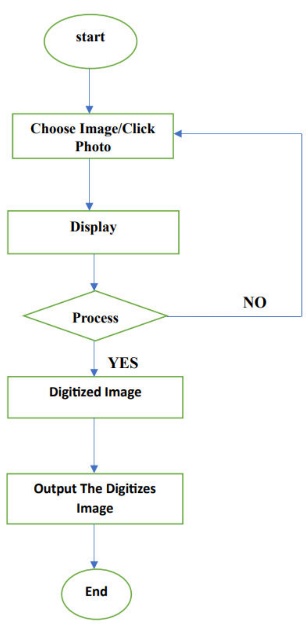

Fig .1. Input from app.

The process for digitizing ECG signals (Figure 1) begins with the user selecting or capturing an ECG signal image. Once the image is obtained, it is displayed for further analysis. At this point, the user has the option to proceed with processing the displayed image. If the user chooses to do so, the image undergoes the digitization process, where the analog ECG signal is converted into a digital format appropriate for computerized analysis. Finally, the digitized image, representing the ECG signal in a digital form, is outputted or saved for further analysis or storage. This workflow is crucial for analyzing and interpreting ECG data in a digital environment, facilitating more efficient and accurate diagnostic procedures.

B. User interface:

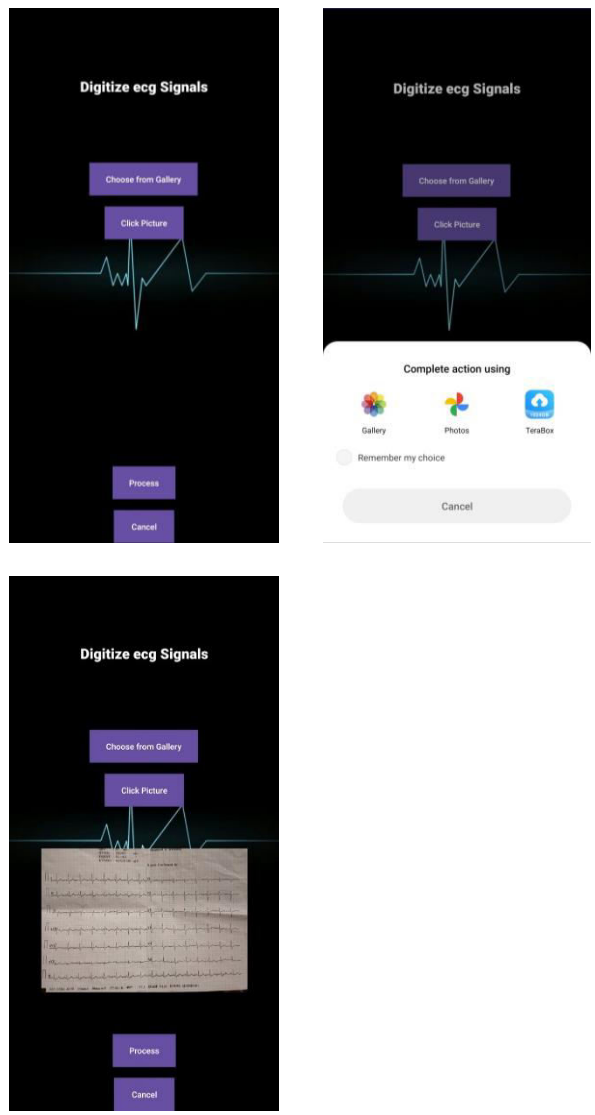

Fig .2. Input from app.

C. Image Processing Results:

The application of simple thresholding effectively separated the ECG signal from the background, creating a binary image where the signal was represented by white pixels and the background by black pixels.

Fig .3. Result of Simple thresholding

Otsu's thresholding method is essential in processing ECG signals, separating the signal from background noise effectively. This method calculates the optimal threshold value to distinguish the ECG signal from noise, enhancing signal quality for analysis. By maximizing the variance between signal and noise, Otsu's method provides clear segmentation of the ECG signal, ensuring only relevant components are retained. This segmentation is crucial for accurate interpretation of ECG waveforms, identifying features like P, QRS, and T waves. Otsu's method enhances accuracy and reliability of ECG signal processing, aiding in precise diagnosis and monitoring of cardiac conditions [7].

In image processing, Otsu's method automatically computes the threshold to convert a grayscale image into a binary image. The algorithm assumes that the image to be thresholder contains two classes of pixels. The within-class variance, defined as the weighted sum of variances of each cluster object (O) and background (B), is minimized to find the optimal threshold value. This approach provides a robust and efficient method for thresholding, particularly beneficial in ECG signal processing and other image analysis applications.

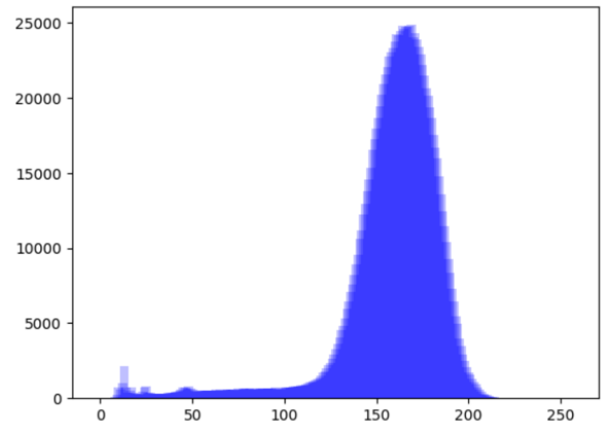

Fig .4. After Otsu's thresholding.

The non-local means denoising algorithm relies on a neighborhood of pixels centered around a target pixel *p*, denoted as B(p*r*), with a size of $(2r + 1)$ x $(2r + 1)$ pixels [8]. This research focuses on a square neighborhood of fixed size due to computational constraints, typically using a 21x21 window for small and moderate values of *r* and a 35x35 window for larger values of *r*. The algorithm's effectiveness in reducing noise is based on the weighted comparison of color patches centered at pixels *p* and *q*, allowing for the identification of similar pixels and the reduction of noise in the ECG signal.

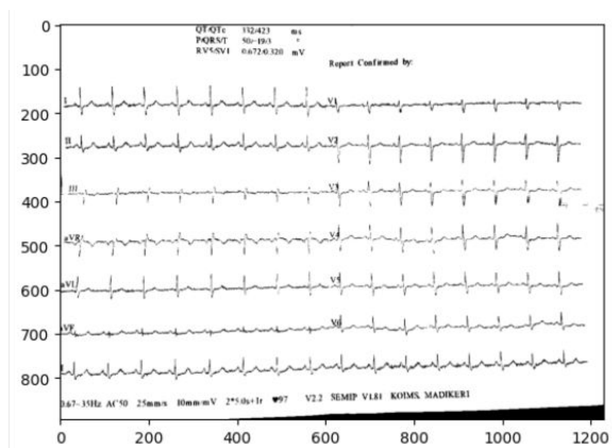

Fig .5. Enhanced image after non-local means denoising

Signal Extraction and Time Scale Division:

The successful extraction of the one-lead ECG signal involved the identification and storage of black pixel positions representing the signal. This data served as the foundation for reconstructing the ECG waveform. The preparation of the ECG data encompassed several steps, including the selection of appropriate beats and the removal of various artifacts. Techniques such as baseline wander correction, DC shift removal, elimination of power-line noise, and mitigation of high-frequency interference were applied (Maglaveras, 1998; Haykin, 2001; Ma et al., 1999). While standard ECG machines typically operate within a bandwidth of 0.05 to 150 Hz, the severity of noise in the palm ECG necessitated a band-limited signal within the frequency range of 1 to 50 Hz [9].

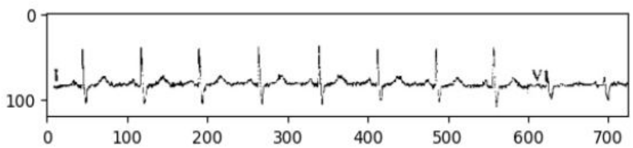

Fig .6. Result of one-lead signal extraction

The algorithm iterates over the columns of the digitized ECG signal image, identifying the positions of each ECG pulse within the signal. By detecting the first occurrence of a black pixel in each column, which represents the presence of an ECG pulse, the algorithm effectively separates each pulse from the adjacent ones. This process is crucial for accurately analyzing and interpreting the ECG signal, as it allows for the isolation of individual pulses for further processing and analysis. In cases where a pulse is not visible in a particular column, the algorithm intelligently uses the positions of the previous pulse to maintain a consistent time scale division, ensuring the integrity of the signal's temporal information.

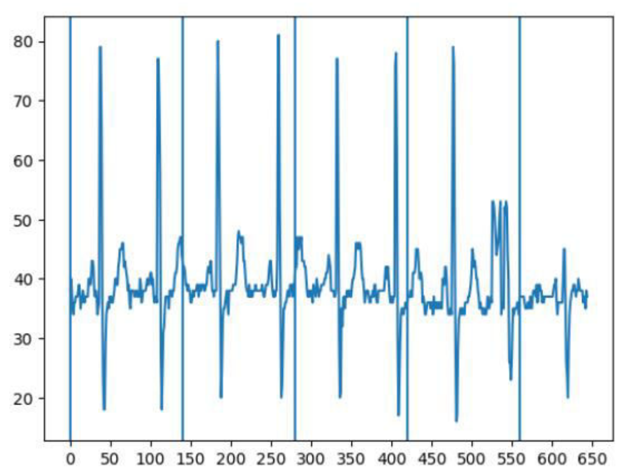

Fig .7. Output of digitized ECG signals.

C. Output in application:

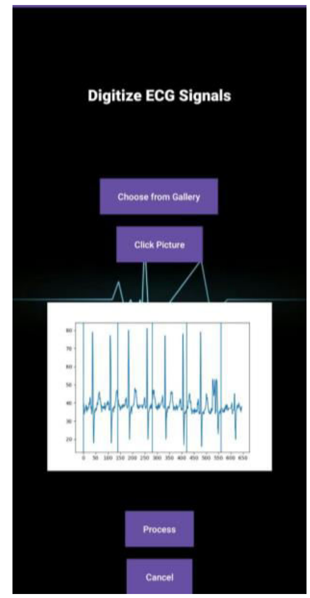

Fig .8. Output of digitized ECG signals in app.

The combination of these image processing techniques resulted in a high-quality, denoised ECG signal that was accurately extracted from the input image. The extracted signal maintained its integrity and structure, allowing for reliable analysis and digitization of the ECG signal.

V. CONCLUSION

In this study, we have presented a comprehensive framework for digitizing ECG signals, integrating sophisticated methodologies for signal extraction, denoising, and preprocessing. The application of Otsu's thresholding method has significantly improved the segmentation of ECG signals from noise, enhancing the quality of extracted signals for further analysis. Non-local means denoising has played a crucial role in reducing noise interference, resulting in clearer and more reliable ECG signals. The utilization of one-lead signal extraction processes has enabled the accurate identification and storage of ECG signal data, providing a solid foundation for signal reconstruction. Moreover, our preprocessing techniques, including beat selection and artifact removal, have ensured the extraction of high-quality ECG data for diagnostic purposes. This research contributes to the advancement of ECG signal processing, offering valuable insights for enhancing diagnostic precision and patient care in cardiology.

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