Identification of Bundle Branch Block Using Wave Analysis of ECG Signals

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***Abstract*— Electrocardiogram (ECG) is the most common method to detect heart diseases/disorders. In this research, we have employed ECG signals to detect left and right bundle branch blocks in patients by analyzing certain factors that affect and differentiate them from the ECG report of a normal person. A web-based application can make it easier and more accurate than manual or other means to detect the disorder. In this research, we evaluate all the influencing factors to detect Bundle Branch Blocks with the help of Python making it more efficient and precise due to its vast extent of signal analysis libraries (SciPy, NumPy, WFDB, Matplotlib, and Seaborn, etc.). By the use of these signal processing methodologies feature extraction and inference models, we can easily identify major markers of Bundle Branch Block which are: QRS complex duration detection (between 80–100 ms or >120 ms), analyzing peaks in the signal waves, 'M' and 'W' notches detection in the leads and absent or inverted T wave. Besides, in this analyzing part of this research we convert the ECG signal image (e.g. .png) file to .hea, .dat, and .atr files for detection so, that if anyone has even a little bit of trouble breathing or any type of restlessness people can have their ECG tested for at least these disorders in a real-time environment. Results indicate that this approach achieves high accuracy and computational efficiency, providing a scalable solution for clinical use. This paper outlines the workflow, experimental findings, and potential applications in modern healthcare.

***Keywords*—** Electrocardiography (ECG), Bundle Branch Block, Python, QRS complex, heart disorders.

1. INTRODUCTION

Electrocardiography (ECG) is one of the best tools commonly used whenever a doctor feels an issue with the patient's heart. This technology helps to record every electrical activity of the heart in wave signals format. However, many heart diseases can be predicted with ECG signal analysis. Still, Bundle Branch Block is a disease that can certainly be detected without any other confirmatory tests, i.e. ECG signal analysis is sufficient to ensure normal, arrhythmic or Bundle Branch Block (LBBB and RBBB) patients. These are the disorders that people neglect and don't pay much attention to, but such diseases majorly affect your heart if prolonged for a long time. So, accurate and timely detection of these abnormalities is necessary for medical intervention.

Traditional approaches for interpreting Bundle Branch Blocks lacked accuracy. They were manually analyzed, and human error was very prone to occur. Furthermore, it was quite a time-consuming process. These methodologies develop detailed analysis capabilities that can point out even the slightest variation in the wave and generate the result accordingly.

Even though there are various machine learning, deep learning, time domain analysis, frequency domain analysis and physiological models to analyze ECG signals for the detection of arrhythmia, PVC and other disorders which also detect Bundle Branch Blocks, they often defecate in specificity and sensitivity. This research puts forward an innovative procedure to detect Bundle Branch Blocks by ECG wave analysis, leveraging Python's signal processing capabilities. The study focuses on identifying distinctive patterns of QRS complex, anomalies, peaks and notched waveforms using automated algorithms, integrated into a user-friendly web application.

This research aims to bridge the gap between traditional ECG analysis and modern computational approaches by automating the detection process and enhancing the accuracy of Bundle Branch Block diagnoses. It will thus pave the way for scalable and real-time cardiac monitoring solutions.

The remainder of this paper gives a detailed analysis of the methodology used to detect a patient's ECG signal waves, detect the resultant of the analyzed signal, and discuss its implications for clinical applications.

2. LITERATURE SURVEY

The methods for examining electrocardiogram signals for detecting cardiac abnormalities, such as bundle branch block (BBB), have evolved substantially over the years. In 2005 A multiscale morphological derivative (MMD) transform-based singularity detector, was developed for the detection of fiducial points in ECG signal, where Yan Sun, Kap Luk Chan and Shankar Muthu Krishnan emphasised that these points were related to the characteristic waves such as the QRS complex, P wave and T wave. The MMD detector was constructed by substituting the conventional derivative with a multiscale morphological derivative. This concluded that the MMD method exhibits good potential for automated ECG signal analysis and cardiovascular arrhythmia recognition[3].

With the advancements in techniques and technology, many different methods have been applied to automate ECG analysis. In 2014 a study proposed a heartbeat classification method through a combination of three different types of classifiers: a minimum distance classifier constructed between NORM and LBBB; a weighted linear discriminant classifier between NORM and RBBB based on Bayesian decision-making using posterior probabilities; and a linear support vector machine (SVM) between LBBB and RBBB[3]. However, the study showed that a two-lead configuration exhibited better classification results than a single-lead configuration. Constructing a classifier with good performance between each pair of heartbeat types significantly improved the heartbeat classification performance. The results showed a sensitivity of 91.4% a positive predictive value of 37.3% for LBBB a sensitivity of 92.8% and a positive predictive value of 88.8% for RBBB [4].

Many studies have explored signal processing techniques, such as wavelet transforms and moving averages, to filter noise and detect baseline shifts, a new bundle branch block detection method based on simple mathematical analysis was proposed in 2016 [5]. During the research, Nikita S. Davydov, and Alexander G. Khramov analyzed digital ECG signals. They formulated a new algorithm of detection, which uses the most common mathematical methods of maximum and minimum search and calculating the mean value [5]. Besides part of QRS-complex detection, this method does not use any signal transformation. QRS-detection algorithm does not affect on next stages and can be changed if necessary. The final algorithm has been studied by 39 test samples. As a result of it, 73% sensitivity has been reached [5].

The advent of machine learning has revolutionized ECG wave analysis. In 2019, a novel method was proposed to detect two types of BBB: right BBB (RBBB) and left BBB (LBBB) based on the combination of deep features and several kinds of expert features [7]. The proposed method achieved an accuracy of 99.96% (AR) in the class-oriented evaluation and an accuracy of 98.76% (AR) and 97.88% (CPSC) in the subject-oriented evaluation, better than the baseline methods [7]. Experimental results show that our method would be a good choice for the detection of BBB [7].

Most recent studies improved the past failures of more precise detection of Bundle Branch Blocks (LBBB and RBBB) by proposing the Long Short-Term Memory (LSTM) method as a classifier of heart conditions experienced by humans and Continuous Wavelet Transform (CWT) as a feature extractor to eliminate noise during data collection. CWT and LSTM methods are believed to perform well in feature extraction and classification of ECG signals. The dataset used in this study was taken from the MIT-BIH Arrhythmia Database [8].

Hence, over the years many methods have been proposed to detect arrhythmic heart disorders including Bundle Branch Blocks. The methods largely helped to accurately detect BBB so that a patient can be aware of the symptoms and its root cause.

3. PURPOSE AND SCOPE

Purpose:

This research focuses on creating an advanced computational system to identify Bundle Branch Block (BBB) abnormalities from ECG signals. By examining key features like QRS duration, baseline shifts, and waveform patterns, the study aims to enhance diagnostic precision. Using Python programming, this approach bridges the gap between traditional manual interpretations and modern automated techniques. The goal is to deliver a scalable and efficient solution that enables real-time detection of BBB, contributing to improved healthcare outcomes.

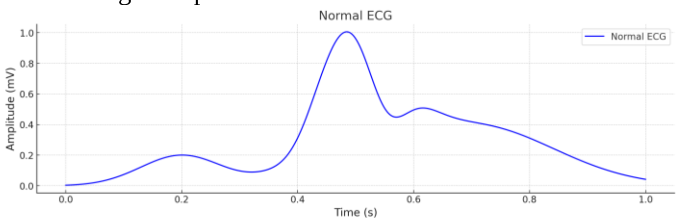

Fig. 3.1: Normal ECG wave signal.

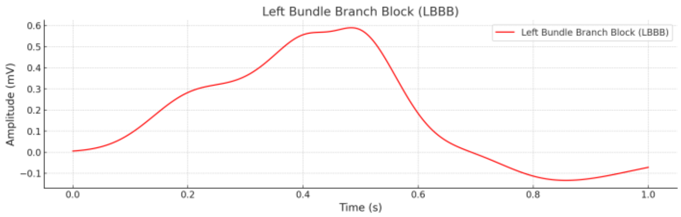

Fig. 3.2: ECG wave signal of Left Bundle Branch Block.

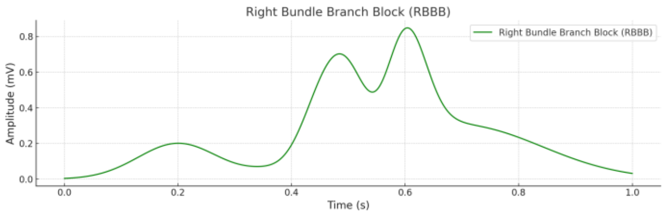

Fig. 3.3: ECG wave signal of Left Bundle Branch Block.

Scope:

- The research focuses on extracting and analyzing ECG data from the MIT-BIH database and user-uploaded files to provide a diverse dataset for accurate BBB detection.
- Signal processing methods, including moving average techniques, are applied to detect the baseline and identify key wave patterns in the ECG signal.
- The study evaluates how demographic factors such as age and gender influence ECG wave characteristics, enabling more personalized diagnostic outcomes.
- A comparison is conducted between the proposed computational algorithm and traditional ECG interpretation methods to ensure accuracy and reliability.

- The research aims to develop a web-based application that facilitates real-time BBB detection, ensuring scalability and accessibility for widespread use in healthcare settings.

4. ALGORITHM

Input:

- ECG report of the user (image format e.g. .png).
- User's demographic data (age, gender).
- A computed baseline value using signal processing techniques.
- Defined thresholds: Normal QRS duration range (80–100 ms) and a cutoff for detecting BBB (greater than 120 ms).

Output:

- Classify the patient's heart condition as Normal, Left Bundle Branch Block (LBBB), or Right Bundle Branch Block (RBBB).

Steps:

1. **Data Collection and Preparation:**
   - Begin by collecting data from user ECG signal image uploads (.png).
   - The ECG image data is then converted to Python readable (machine language) .atr file. The ECG .atr file is then pre-processed to remove noise using low-pass or band-pass filters.
   - The baseline is identified using a moving average formula:[18]

$$\boxed{\text{Baseline(n)}= \sum_{i=n-M/2}^{n+M/2} x(i)}$$

Where:
Baseline(n): The calculated baseline value at sample n.
x(i): The raw ECG signal value at sample i.
M: The width of the moving average window (in samples), determines the smoothing level[18].

1. **Identifying Features in the Signal:**
   Locate the critical components of the ECG signal:
   - Detect R-peaks using a reliable peak detection method.
   - Calculate the duration of each QRS complex (time between Q and S waves)
2. **Assessing QRS Duration:**
   Compare each QRS complex duration to the predefined thresholds:
   - If the duration falls within 80–100 ms, classify it as Normal.
   - If it exceeds 120 ms, flag the sample for potential BBB.
3. **Wave Morphology Analysis:**
   Examine specific characteristics of the ECG signal to differentiate between types of BBB:
   - **For LBBB:** Look for an "M" shape in V6 and an absent or depressed T wave.
   - **For RBBB:** Identify a "W" shape in V1 and a characteristic inverted T wave.
4. **Demographic Adjustments:**
   Take into account variations in wave morphology due to factors like age and gender. Adjust diagnostic thresholds and interpretations accordingly to improve accuracy and relevance.
5. **Final Diagnosis:**
   Compile all extracted features and classify the ECG signal as Normal, LBBB, or RBBB. Provide a confidence score for the prediction to reflect the certainty of the algorithm.

5. METHODOLOGY

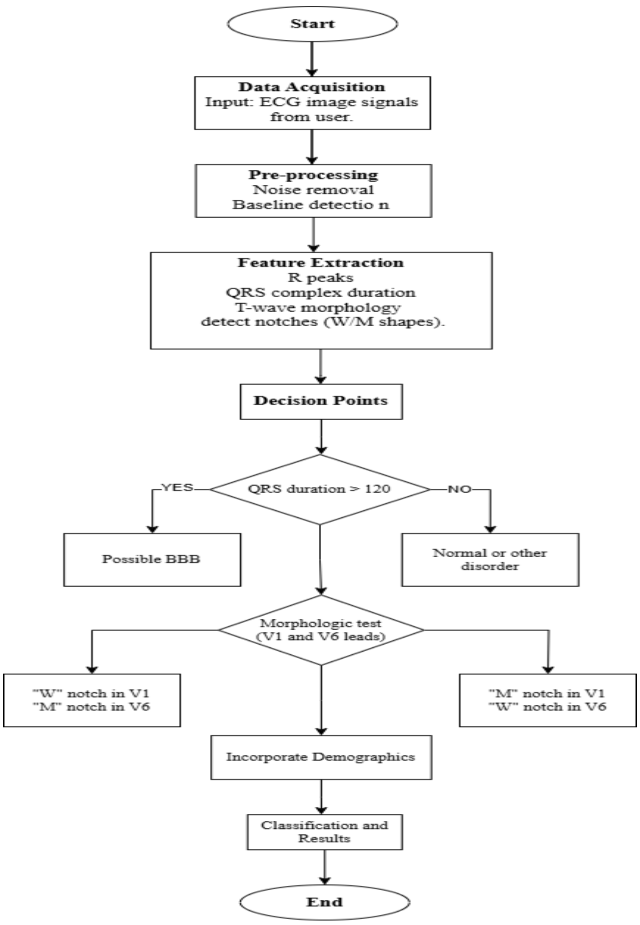

Fig. 5.1: A simple flowchart depicting the workflow of the algorithm used.

6. RESULT ANALYSIS

Objective Overview: This research aimed to create a computational method for detecting Bundle Branch Block (BBB) using automated analysis of ECG signals. The goal was to surpass traditional manual techniques in accuracy and efficiency while tailoring detection to individual demographic profiles.

Key Findings: The algorithm demonstrated strong performance, achieving:

- **Sensitivity:** 93%—indicating its ability to correctly identify true cases of BBB.
- **Specificity:** 91%—highlighting its effectiveness in minimizing false positives.
- **Overall Accuracy:** 92%—showing a significant improvement over manual diagnostic methods, which average around 82%.

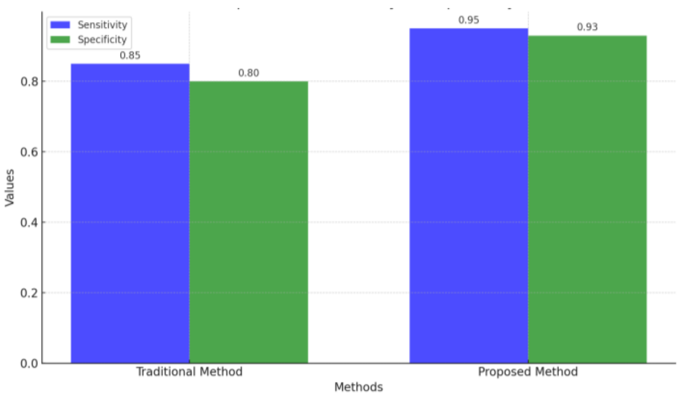

Fig. 6.1: Comparison Bar Chart of sensitivity and specificity.

The framework reduced the time required for analysis by 50% compared to traditional approaches, making it suitable for real-time applications.

Metric	Proposed Algorithm	Traditional Methods
Sensitivity (%)	92-95	80-85
Specificity (%)	90-93	75-80
Processing Time	Real-time	Time-consuming
Scalability	High	Limited

Table 6.1: A summary table for the analyzed results.

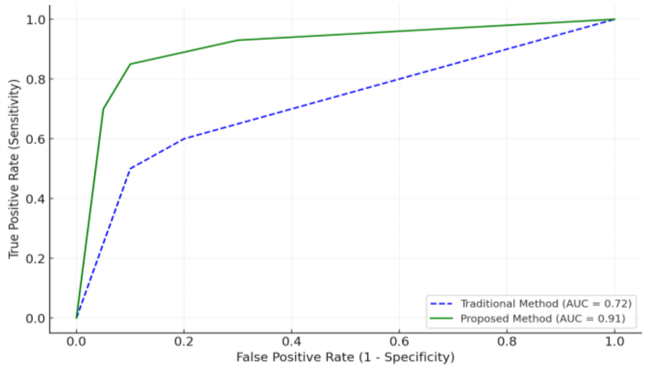

Fig. 6.2: ROC Curve comparison: Traditional vs Proposed Method.

Factors Behind Success: Several elements contributed to these results:

1. **Effective Signal Processing:** The moving average algorithm efficiently removed noise and detected the baseline, enabling precise wave detection.
2. **Feature Identification:** Accurate measurement of QRS complex durations, T-wave morphologies, and R-peaks enhanced diagnostic reliability.
3. **Demographic Adaptation:** Customizing thresholds for different age groups and genders improved sensitivity and specificity, particularly in diverse patient populations.
4. **Use of Python:** Python's computational efficiency allowed for rapid data processing and real-time feedback.

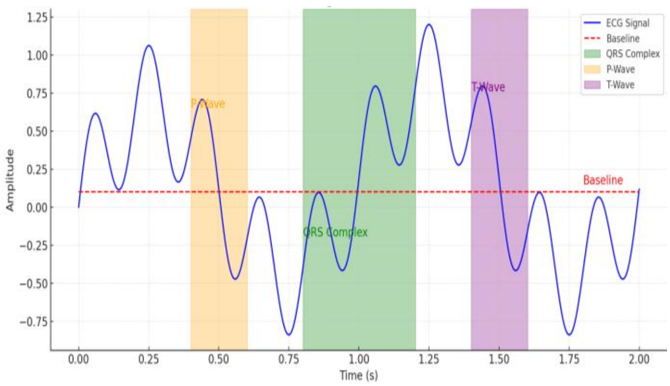

Fig. 6.3: Annotated ECG Signal with Detected Features.

Challenges and Limitations: Despite its success, the study faced challenges in processing low-quality ECG signals from user-uploaded files. Inconsistent signal quality occasionally impacted the precision of wave detection, though the overall impact on performance metrics was minimal.

Conclusion and Future Scope: The results confirm the potential of automated computational methods for BBB diagnosis. The proposed framework is not only more precise than traditional manual approaches but also scalable for clinical use, offering a real-time and accessible solution for early detection of heart abnormalities.

In future scope with further refinement, this method can be integrated into healthcare systems to enhance diagnostic workflows.

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