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## Automated Heart Rate and QRS Axis Classification on Digital Electrocardiograms to Determine Associated Disease

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### ABSTRACT

A computational tool was developed in Python to automatically analyze digitized electrocardiograms (ECGs) from the PhysioNet database. Open-source libraries such as NeuroKit, SciPy, and BioSppy were employed to detect fiducial points corresponding to the P wave and QRS complex. Based on these measurements, temporal intervals within the ECG were extracted to estimate heart rate, cardiac rhythm, and electrical axis, thus allowing the identification of potential underlying cardiac abnormalities. The proposed script demonstrated the ability to accurately detect conditions including bradycardia (mild, moderate, or severe), tachycardia, rhythm classification (regular or irregular), and electrical axis orientation (normal, leftward deviation, rightward deviation, or indeterminate). In this preliminary testing phase, a total of 100 ECGs were analyzed. From these, 60% were classified as bradycardia, 10% as tachycardia, 30% as normal frequency; on the other hand, electrical axis was classified as leftward (20%), indeterminate (20%) deviations and 60% as normal, while no rightward deviations were observed. Examples of specific cardiac conditions identified by the algorithm include Left Ventricular Hypertrophy (LVH), Sinus Node Dissociation (SND) and electrical instability (EI). These results were validated by a cardiologist from Hospital General Desiderio Rosado Carvajal in Comalcalco, Tabasco, Mexico, who performed the analyses through conventional diagnostic methods and, in all cases the predictions were exactly equals. The high accuracy observed supports the potential of this computational approach as a technological aid in clinical settings.

### INTRODUCTION

The number of deaths caused by heart diseases has remained remarkably high in recent years. It is estimated that over the past five years, more than 80 million people have died worldwide due to cardiovascular conditions (Organization, 2025), (Roth, 2020), representing approximately 32% of global mortality. Consequently, major efforts are being made to mitigate this public health problem. One of the most effective tools available for analyze the behavior of the human heart is the electrocardiogram (ECG), which measures the electrical depolarization and repolarization of the atria and ventricles. The ECG is a non-invasive, easy-to-use, and cost-effective diagnostic method. This electrical signal produces a P wave, a QRS complex, and a T wave, whose morphology provides valuable information about potential cardiovascular abnormalities. Depending on certain conditions, the risk level can be classified as low, medium, or high (Sun, 2012). Some of the conditions that may indicate cardiovascular risk include inadequate blood flow in the coronary artery, electrolyte imbalances, second- and third-degree atrioventricular blocks, bundle branch blocks, hypertension, cardiomyopathies, and valvular disorders (Singh, 2023), (Ahmad, 2021), (Golgowsky, 2020). To achieve a reliable diagnosis, the ECG signal must be clean—that is, free from noise or interference. In many cases, improper electrode placement can lead to signal corruption due to involuntary patient movement

or even interference from the electrical network powering the equipment (Ahmed A. Ali, 2023), (Huang Y. Liu, 2021). The use of band-pass filters makes it possible to minimize most of these noise sources (Kramer, 2022). Among them are filters based on the Fourier transform (Kumar, 2019), finite impulse response filters (Almalchy M. C., 2019), Kalman filters (Hesar, 2017), discrete wavelet transform (Hashim, 2017), and Savitzky–Golay filters (Sultana, 2015), among others. The denoising process is of fundamental importance for the analysis and correct interpretation of digital ECG signals (Kosinski, 2013). The accuracy and efficiency of ECG analysis can be significantly improved when computational analysis is applied, allowing for almost instantaneous results and automatic measurement of various parameters (Zavadzil, 2024), (Ansari, 2023). In (Achayra U. Oh, 2017) states that most of these challenges occur mainly in developing countries due to the lack of sufficient resources for acquiring equipment or medication. Furthermore, most electrocardiographs contain proprietary software, which makes it difficult to obtain electrical data in a simple and free manner. For this reason, several researchers have developed a variety of open-access software tools that enable the scientific community to analyze ECG signals efficiently. Such is the case of (Roberts, 2024), who developed open-source software that uses a single ECG lead (Lead II) to measure respiratory rate. One of the most widely used algorithms for calculating heart

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rate, cardiac rhythm, and QRS complex duration, among other parameters, is the Pan–Tompkins algorithm (T. Rodrigues, 2021). The extraction of these parameters is based on the analysis of slope, amplitude, and QRS duration. This algorithm has been implemented in Python by (Wicaksana, 2019) and (Lee S. J., 2018). A research group led by (Milivojevic, 2017) reported that Python is a highly attractive programming language for analyzing biological signals due to its large number of specialized libraries. In particular, they used the BioSPPy package to determine heart rate and cardiac rhythm by analyzing the frequency spectrum of the signal, since this library includes numerous pattern recognition algorithms for biomedical signal analysis. On the other hand, Nguyen (Nguyen, 2021) employed the NeuroKit2 library to extract cardiac features under three different physiological states—resting, walking, and running. In addition, a comparative study between NeuroKit2 and the Kalidas software package (Nabian, 2018) revealed that NeuroKit2 is significantly

faster at extracting ECG information.

### Traditional Measurements

Traditionally, cardiologists measure and classify heart rate, cardiac rhythm, and the electrical axis by observing the ECG printed on the grid paper. For example, to measure rhythm and heart rate, they count the number of small boxes between one QRS complex and the next, using lead II (Goldberger, 2023). In the case of the electrical axis, they observe whether the QRS is positive or negative in leads I and aVF; from there, they identify the axis deviation, whether it is left, right, indeterminate, or normal (Thaler, 2018). In Figure 1, we can observe an ECG with Left Shift Axis (QRS positive on DI lead and QRS negative on aVF lead), regular rhythm (because the R-R intervals are constant) and 60bpm (count the numbers of QRS at 6s, and multiply by 10; DII lead). An experienced cardiologist could take as little as 20s to obtain these values accurately.



**Figure 1:** ECG with Left Shift Axis (Zheng, 2025).

### MATERIALS AND METHODS

For the development of this study, the dataset entitled “A Large-Scale 12-Lead Electrocardiogram Database for Arrhythmia Study” was downloaded from PhysioNet (Zheng, 2025). Each signal comprises 12 leads (DI, DII, aVF, etc.), sampled at 500 Hz for 10 seconds. The creation of this dataset was supported by Chapman University and Shaoxing People’s Hospital. The electrocardiograms were analysed using a Python-based code developed by the authors, employing various libraries such as NumPy, Pandas, SciPy, BioSPPy, NeuroKit, among others. The algorithm used to determine heart rate, cardiac rhythm, and electrical axis follows the same procedure traditionally applied by cardiologists. Specifically, lead II was analyzed to calculate the first two variables (heart rate and rhythm), while both lead II (DII) and aVF were used to determine the cardiac electrical axis. The identification of possible diseases associated with the extracted parameters was validated by a specialist in the field. The algorithm begins by extracting ECG data and proceeds with a signal cleaning process using the Savitzky–Golay filter with a window size of 21 and a polynomial degree of 11 (Sandoval, 2025), as it provides a correlation coefficient close to unity, signal-to-noise ratios greater than 20 dB, and a very low mean

square error. The detection capability of the proposed algorithm was evaluated in terms of sensitivity and false positive rate (Pascual Huerta, 2024), using the following expressions:

$$\text{Sensitivity} = \frac{\text{True Positive}}{(\text{True Positive} + \text{false negatives})} \quad (1)$$

$$\text{false positive rate} = 1 - \text{specificity} \quad (2)$$

Sensitivity values close to unity indicate high prediction accuracy, whereas a false positive rate approaching zero implies minimal errors in the algorithm’s output. Both metrics were applied to evaluate heart rate, cardiac rhythm, and the electrical axis.

### RESULTS AND DISCUSSION

Algorithm 1 shows the steps used to calculate and classify ECG frequencies, as well as to identify cardiac rhythm and electrical axis. The process begins with reading the ECG signal using the SciPy library. Subsequently, a Savitzky–Golay digital filter with a window size of 21 and a polynomial order of 11 is applied to minimise the noise that may be present in the original signal.

**Algorithm 1:** Basic Electrocardiographic Analysis

**Input:** Raw electrocardiographic signal

**Output:** Electrocardiographic parameters and potential

identification of cardiac pathologies

- Start
- Acquire the raw electrocardiographic signal.
- Apply signal processing and filtering techniques to suppress noise and artifacts.
- Analyze Lead II:
- Compute the heart rate.
- Assess cardiac rhythm.
- Analyze Leads I and aVF:
- Determine the cardiac electrical axis.
- Analyze the extracted electrocardiographic parameters:
- Evaluate the presence of potential underlying cardiac conditions.
- Present the analysis results.
- End

From this point, lead II (DII) is selected to determine heart rate and rhythm. In this lead, R waves and their respective positions are detected to measure the distance between them, allowing for the calculation of the previously

mentioned parameters (see Table 1). The determination of the cardiac electrical axis is performed by analysing the amplitudes (mV) of the R and S waves in leads II and aVF from QRS complex. Depending on these values, the axis can be classified as normal, left-deviated, right-deviated, or indeterminate (Pérez Villareal, 2023). A combination of the previously obtained parameters provides indications of potential associated cardiovascular condition such as left ventricular hypertrophy (LVH), left anterior fascicular block (LAFB), Sinusal Node Diseases (SND), among others. For instance, an ECG showing a heart rate of 56 bpm, a leftward axis deviation, and a regular rhythm may suggest LVH or LAFB, corresponding to a moderate-risk level. It is important to note that the above interpretation, as well as those presented in Table 2, were validated by a cardiologist from Hospital General Desiderio Rosado Carvajal.

The developed code automatically performs all parameter calculations; that is, the user simply selects the file

**Table 1:** Classification of heart rate

| Interval (bpm)  | Classification             |
|-----------------|----------------------------|
| Freq < 40       | Severe bradycardia (SeB)   |
| 40 < Freq < 50  | Moderate bradycardia (MoB) |
| 50 < Freq < 60  | Mild bradycardia (MiB)     |
| 60 < Freq < 100 | Normal frequency (NF)      |
| Freq > 100      | Tachycardia (Tq)           |

containing the digitised ECG, executes the code, and the results are displayed in a CSV file. Initially, an SG(21,11) filter was applied to reduce the noise in the signal, achieving a correlation coefficient of 99%. As shown in Figure 2, this filter preserves the morphology of the original signal—that is, no significant distortions are observed in the amplitude of the involved waves, in the frequency, or in the amplitude of the QRS complex, both

in time and voltage domains (the latter being particularly important for identifying certain types of blocks or hypertrophies). Moreover, the filter effectively reduces background noise. These characteristics enable the highly reliable application of the aforementioned libraries for obtaining the fundamental parameters representative of the ECG.

A total of 100 ECGs with different cardiac conditions

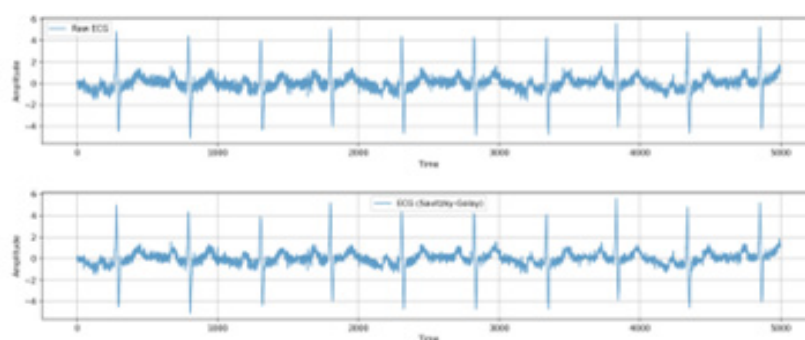


**Fig 2:** SG(21,11) filter applied to an ECG

were analysed. The code detected regular and irregular mild bradycardia in 60% of the cases, normal regular and irregular frequencies in 30%, and tachycardia in 10%. Regarding the electrical axis, 60% were classified as normal, 20% as left-deviated, and 20% as indeterminate. No severe bradycardia or right-axis deviation was found within this population, although the algorithm is designed to detect them. Table 2 show the results obtained by the algorithm, indicating the electrical axis, cardiac rhythm,

heart rate value, frequency classification, associated disease, and risk level for each case.

Five diseases were identified as associated with combinations of heart rate, rhythm, and electrical axis parameters: two cases were related to LVH/LAFB (moderate-risk), two cases corresponded to SND (moderate-risk), and one case showed possible electrical instability, classified as high-risk. All of 100 ECGs were

**Table 2:** Classification of heart rate

| Electrical Axis | Rhythm    | Frequency (bpm) | Classification of frequency | Associated Disease     | Risk Level |
|-----------------|-----------|-----------------|-----------------------------|------------------------|------------|
| Normal          | Regular   | 56.7            | MiBR                        | No                     | Low        |
| Normal          | Irregular | 63              | NF                          | No                     | Low        |
| Left            | Irregular | 63              | NF                          | LVH/ LAFB              | Moderate   |
| Indeterminate   | Regular   | 56.7            | MiBR                        | LVH/ LAFB              | Moderate   |
| Normal          | Regular   | 56.7            | MiBR                        | No                     | Low        |
| Normal          | Regular   | 63              | NF                          | No                     | Low        |
| Indeterminate   | Irregular | 56.7            | MiBR                        | Electrical instability | High       |
| Normal          | Irregular | 44.1            | MoBI                        | SND                    | Moderate   |
| Left            | Regular   | 56.7            | MiBR                        | LVH/ LAFB              | Moderate   |
| Normal          | Irregular | 107.1           | Tq                          | No                     | Low        |

independently analysed by a cardiology specialist, who was asked to identify the same parameters as those calculated by the code. It was found that all parameters matched perfectly, indicating that the algorithm predicted heart rate, rhythm, cardiac axis, and associated conditions with an accuracy of 100%, for those cases. Consequently, sensitivity equals one and the false positive rate equals zero, confirming that the calculations and predictions made by our code are highly reliable.

## CONCLUSION

The total execution time of the code for analysing the 100 ECGs was approximately 170 seconds, meaning that each ECG was processed in less than two seconds (a cardiologist spend 20s). These results—validated by a medical specialist—suggest that the code could serve as a supportive diagnostic tool in cardiology, providing preliminary results for each patient and thus reducing the physician's workload. It is important to emphasise that the developed code is not intended to replace cardiology specialists under any circumstances, as numerous cardiac conditions and pathologies cannot be fully represented within the program. A Python-based program was developed using libraries such as NeuroKit2, SciPy, BioSPPy, NumPy, and Pandas, among others. The code automatically detects ventricular frequency, cardiac rhythm, and electrical axis, and identifies potential diseases associated with these parameters or their combinations. The system analyzed 100 ECGs in 170 seconds, achieving a sensitivity of 1.0 and a false positive rate of 0, meaning that all basic ECG parameters were correctly identified in the same way as by the cardiology specialist. Results show that 60% of the population presented mild bradycardia (regular or irregular), 30% had normal heart rate (regular or irregular), and 10% showed tachycardia. Regarding the electrical axis, 60% were classified as normal, 20% as left-deviated, and 20% as indeterminate. No severe bradycardia or right-axis deviation was detected in this sample. Among the various parameter combinations, five pathologies were identified: two ECGs associated with LVH/LAFB (moderate risk), two with SND (moderate risk), and one case showing possible electrical instability,

characterised by mild bradycardia, an indeterminate axis, and irregular rhythm (high risk). Therefore, the developed code can be considered a valuable computational tool to assist cardiologists in ECG interpretation, helping to streamline their workload while maintaining diagnostic accuracy.

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