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Optimization of heart rate measurement using fast Fourier transform modeling on electrocardiogram signals

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ABSTRACT

Heart rate measurement based on electrocardiogram (ECG) signals is commonly performed through traditional observation techniques, which can be less effective especially when restricted to short-range. Such limitations may hinder the detection of subtle variations in cardiac rhythm, potentially resulting in the omission of critical time-dependent physiological information. To overcome this challenge, a computational approach is introduced to enhance both the accuracy and consistency of heart rate estimation. The fast Fourier transform (FFT) is applied to convert ECG signals from the time domain to the frequency domain, allowing for accurate identification of dominant spectral components associated with cardiac activity. This transformation also enables the evaluation of long-range, which is often impractical to analyze using time-domain methods alone. A dataset consisting of ten ECG signal recordings from subjects with normal heart function was utilized. Waveform images were digitized using PlotDigitizer software and further processed in MATLAB through spectral transformation. The resulting frequency components were accurately identified, with a mean absolute error of less than 0.2% when compared to reference values. These results demonstrate the effectiveness of a frequency-based analytical approach in improving measurement precision and promoting efficiency in digital cardiac monitoring. The findings contribute to the development of advanced biomedical signal processing techniques.

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1. INTRODUCTION

Advances in medical diagnostic technology continue to evolve, with cardiac electrical activity monitoring emerging as a widely applied innovation. Cardiovascular diseases remain the leading cause of death worldwide. According to data from the World Health Organization, 17.9 million deaths were recorded in 2019, representing approximately 32% of all global mortality, with 85% resulting from stroke and heart attacks [1]. Key risk factors include lifestyle, occupational stress, and dietary habits [2, 3], underscoring the critical role of early detection in effective clinical management [4-6].

The electrocardiogram (ECG) serves as a fundamental tool for assessing heart function by recording the electrical activity produced during myocardial contraction. These signals, generated through synchronized depolarization, results in measurable voltages on the body's surface in the millivolt range [7]. Due to its non-invasive procedure, rapid execution, and wide diagnostic capabilities - including detection of arrhythmias, coronary artery disease, and structural abnormalities - ECG has become indispensable in clinical settings [8].

Despite its advantages, manual analysis of ECG signals presents several limitations [9]. Noise interference, patient movement, and inconsistent electrode placement can diminish accuracy [10, 11]. In addition, the interpretation process is prone to subjectivity and fatigue, even among experienced clinicians [12]. These constraints have led to increased interest in computational methods that aim to improve both precision and analytical efficiency.

Signal transformation techniques that convert time-domain data into frequency-domain representations have gained recognition for addressing these challenges. Among them, the fast Fourier transform (FFT) offers high efficiency and reliability in isolating dominant spectral components [13]. The analytical workflow typically involves three core stages: data preprocessing, feature extraction, and classification [12]. Numerous studies have demonstrated successful applications of this approach, including blood pressure analysis, detection of sleep apnea, and tumor identification in CT imaging [14-16].

In practical application, the method begins with converting ECG signal graphs into numerical data. The resulting data is then processed using spectral transformation to extract dominant frequency characteristics. This approach is particularly useful for revealing patterns that may not be visible through time-based observation alone [17]. The analysis is structured in sequential steps, from preprocessing through frequency transformation to identification of rhythm abnormalities based on spectral output.

2. THEORETICAL REVIEW

ECG is a diagnostic tool used to detect electrical activity in the heart in the form of a graph that records electrical changes in the heart, which are then linked to time [18]. Conventional ECG machines consist of 12 leads divided into two groups, namely limb leads and precordial leads. Limb leads are further categorized into standard bipolar limb leads (I, II, and III) and augmented unipolar leads (aVL, aVF, and aVR). The precordial leads include V1 to V6 [1]. The limb leads view the heart in the vertical plane, while the precordial leads record the heart's electrical activity in the horizontal plane [19]. The typical ECG waveform obtained from lead II consists of five feature waves P, Q, R, S, and T waves [20].

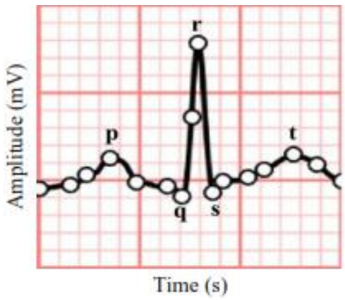


Figure 1. main components of the ECG signal.

FFT is a mathematical calculation method used to convert analog signals into digital signals based on frequency. This method breaks down a signal into different frequencies using complex exponential functions [21]. The Fourier transform consists of representing signals by summing frequencies and amplitudes as follows [13]:

$$f_n = n\frac{F_s}{N} A_n = \sum_{k=0}^{N-1} x_k e^{-\frac{2j\pi kn}{N}} \tag{1}$$

where, f_n is frequency at index n (Hz), F_s is sampling frequency (Hz), n is frequency index, N is number of samples, A_n is amplitude of the spike (mV), and x_k is signal at time k (mV).

3. METHODOLOGY

The FFT method was applied to analyze the frequency spectrum of cardiac bioelectrical signals. Raw data were initially extracted using the PlotDigitizer application, which enabled the conversion of graphical waveform data into numerical values. The resulting dataset, consisting of 110 samples with two columns (time and amplitude), was then exported to Excel format for further processing.

Before transformation, the signal undergoes linear interpolation to ensure uniform time intervals between samples, with the sampling frequency defined as 1000 Hz. A time vector was constructed using a fixed sampling period ($T = 1/F_s$), and the interp1 function in MATLAB was employed to generate a uniformly sampled signal based on the digitized data.

The transformation from the time domain to the frequency domain was performed using the fft() function with 1000 points. Although the NFFT parameter was calculated based on the next power of two, the transform length was explicitly set to 1000 to maintain consistent spectral resolution. The frequency vector ranges from 0 to half of the sampling frequency ($F_s/2$), corresponding to the positive half of the spectrum.

The complex output of the transformation was converted to amplitude and normalized against its maximum value, resulting in a relative power spectrum. This normalization facilitates comparison between different signals. The dominant frequency component, typically associated with heart rate, was identified by locating the highest amplitude peak in the spectrum and was visually highlighted in the frequency plot for easier interpretation.

Figure 2. Fourier analysis.

To represent the ECG signal spectrum based on the results of the transformation from the time domain to the frequency domain, one commonly used approach is the Gaussian model. This model is used for symmetrical shape and suitability for the characteristics of biological signals, which are concentrated at particular frequencies. The mathematical equation is expressed as follows:

$$y(f) = Ae^{-\frac{(f-\mu)^2}{2\sigma^2}} \tag{2}$$

where, $y(f)$ is amplitude at frequency $f(V)$, A is maximum amplitude (V), μ is center frequency (Hz), and σ is spectrum width standard deviation (Hz).

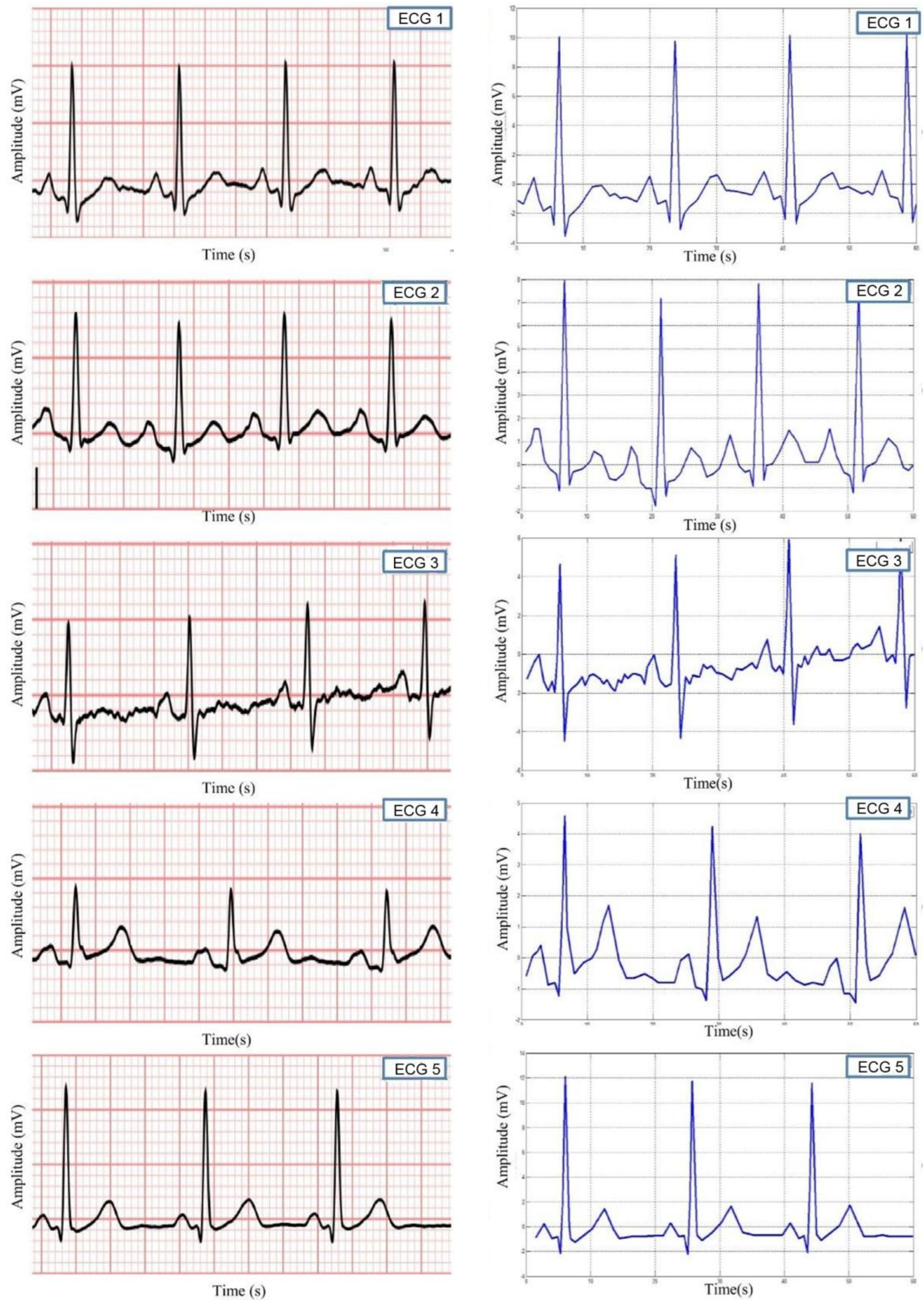
4. RESULTS AND DISCUSSION

This data presents the results of extracting ECG signal data using PlotDigitizer software. The data obtained reflects the waveform of the ECG signal that has been converted into digital form.

Table 1. Numerical values derived from ECG images using PlotDigitizer.

Time (s)	Amplitude (mV)
34.8540146	-0.097561
36.38686131	-0.3170732
37.11678832	-0.902439
37.62773723	3.63414634
37.91970803	7.87804878
38.64963504	-0.6829268
39.16058394	-0.0243902
40.40145985	0.19512195
41.20437956	0.63414634

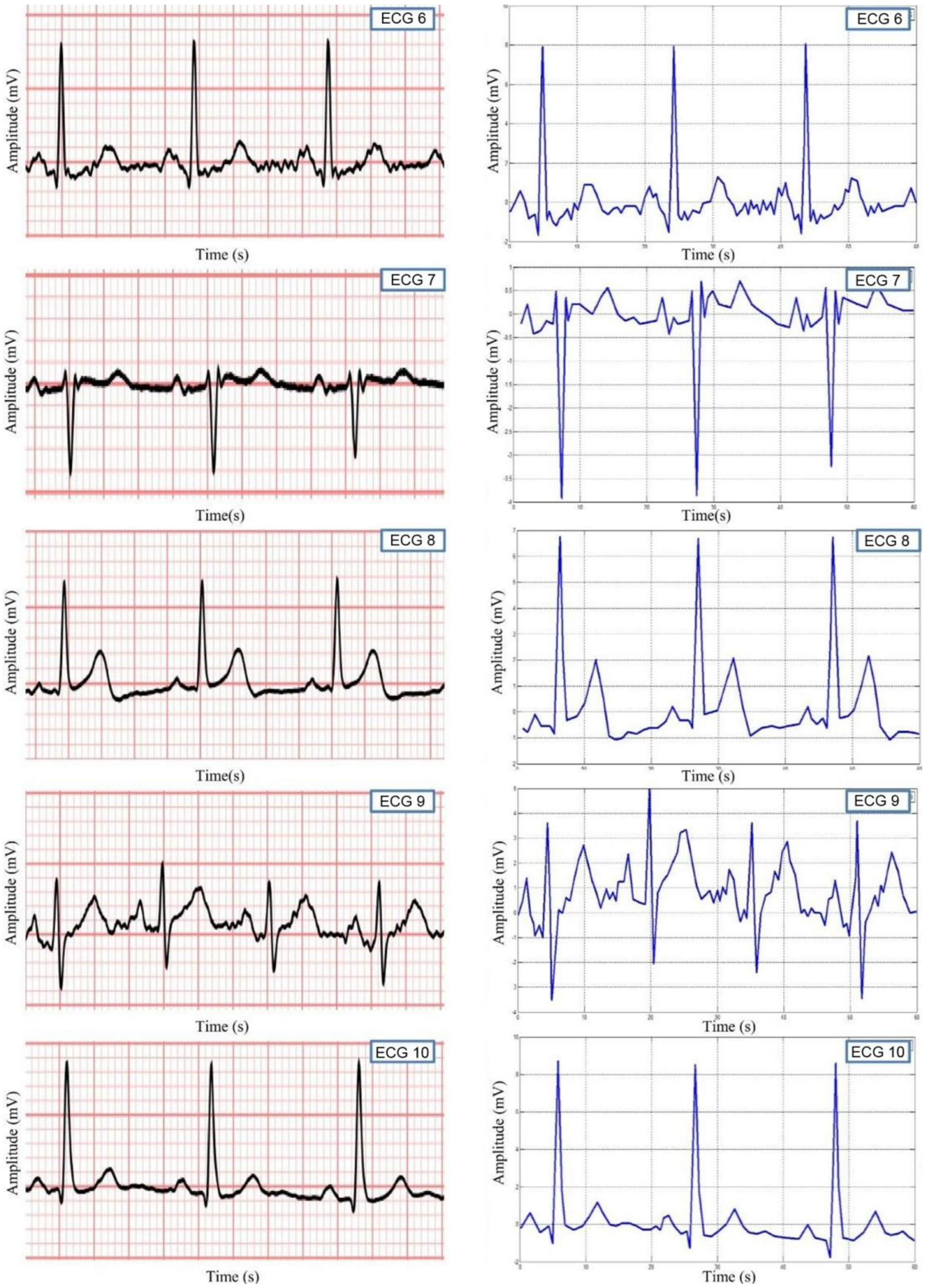
The time function describes the change in voltage with respect to time, while the frequency function describes the distribution of signal energy with respect to frequency. The result of this processing is a heartbeat rhythm graph that shows the distribution of amplitude against time and the frequency spectrum. This information is used to identify the dominant frequency in the ECG signal and analyze the heartbeat pattern based on the characteristics of the resulting frequency spectrum.



(a) (b)

Figure 3. (a) ECG signal data 1 – 5 displayed on standard ECG paper, (b) The result of converting numerical data into heart rhythm from ECG 1 – 5 using MATLAB.

The results of the numerical data conversion using MATLAB in Figures 3 and 4 produce a representation of the heartbeat rhythm displayed in the form of an ECG signal graph. On the graph, the horizontal axis shows time (in seconds), while the vertical axis shows the amplitude of the ECG signal. Visually, it can be observed that all the signals show typical periodic patterns, namely P waves, QRS complexes, and T waves which are the main components in one heart beat cycle [22].



(a) (b)

Figure 4. (a) ECG signal data 6 – 10 displayed on standard ECG paper, (b) The result of converting numerical data into heart rhythm from ECG 6 – 10 using MATLAB.

This section presents the results of transforming ECG signals from the time domain to the frequency domain using the FFT method. This process is done to extract the frequency information from the recorded signal, so that the heart rhythm pattern can be analyzed more clearly. The result is a frequency spectrum graph that shows how the amplitude of the signal changes with frequency. This graph provides an overview of the dominating frequency components in the ECG signal, which will then be used to identify the main frequency patterns.

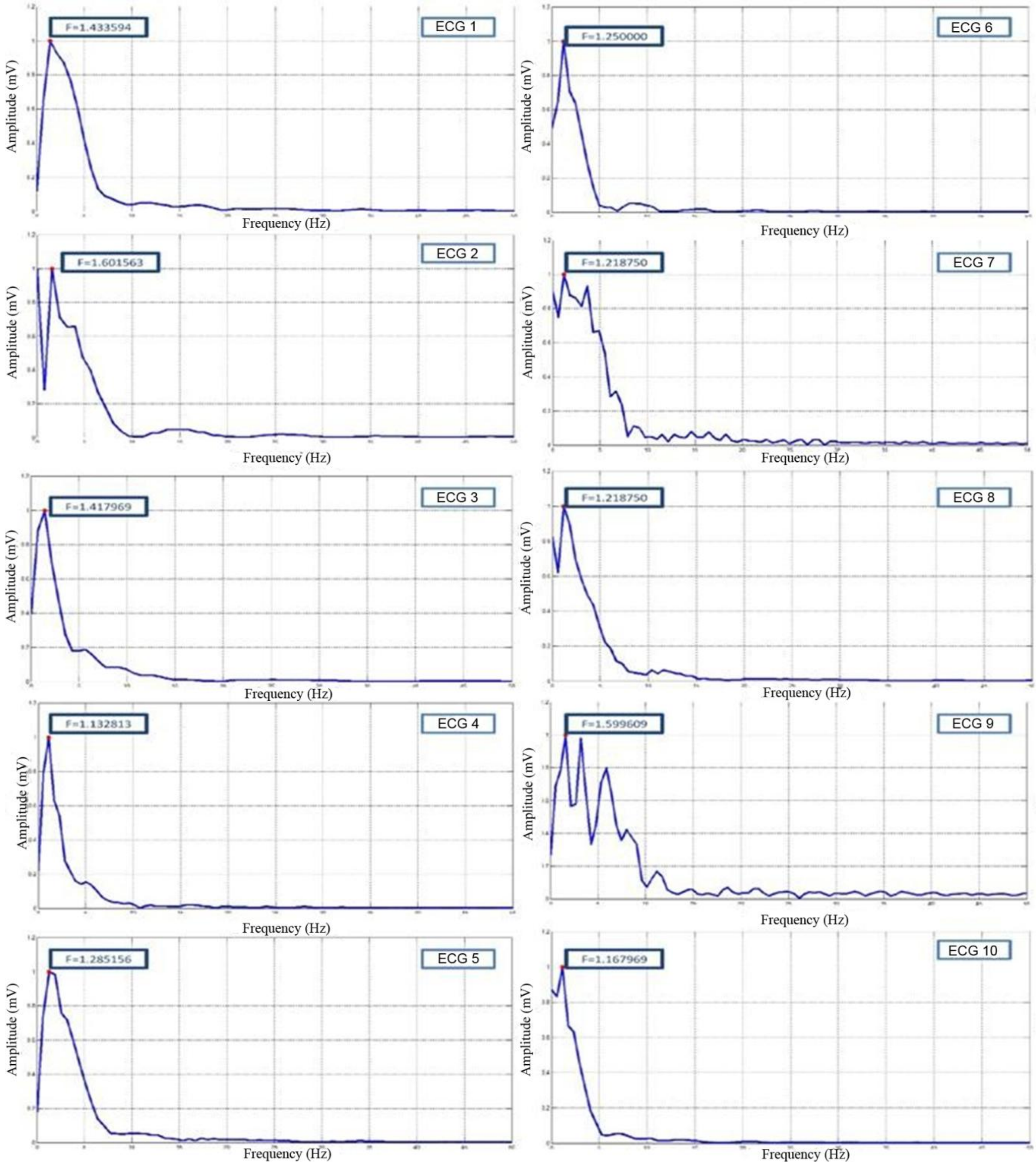


Figure 5. Transformation results of ECG 1 – 10 signals from time domain to frequency domain using FFT.

The analysis results show that all ECG signals have a dominant frequency in the range of 1.1 to 1.6 Hz, which is equivalent to a normal heart rate of 68 to 96 beats per minute. The highest amplitude appears at low frequencies (around 1 – 2 Hz), then decreases sharply after passing the peak, generally in the frequency range of 2 – 5 Hz. Above this range, the amplitude tends to flatten and approach zero, indicating that most of the signal energy is concentrated at low frequencies [23]. However, one sample, ECG 9, shows several additional peaks after the dominant frequency. This condition may indicate the presence of noise or certain complexities in the signal, although it does not significantly affect the identification of the main components. Analysis of the frequency spectrum shows that most of the ECG signal energy is concentrated at low frequencies, consistent with the physiological characteristics of human heartbeats [24]. Thus, the results obtained from the Fourier transform can serve as a basis for further research in the development of an automatic detection system for diagnosing heart disorders. The frequency values for each ECG will be discussed in Table 2.

Table 2. Comparison between FFT results and reference data.

ECG	Heartbeat (bpm)	Frequency result from FFT (Hz)	Heartbeat result from FFT (bpm)	Error (%)
ECG 1	86	1.434	86.040	0.046
ECG 2	96	1.602	96.120	0.125
ECG 3	85	1.418	85.080	0.094
ECG 4	68	1.133	67.980	0.029
ECG 5	77	1.285	77.100	0.130
ECG 6	75	1.250	75.000	0.000
ECG 7	73	1.219	73.140	0.192
ECG 8	73	1.219	73.140	0.192
ECG 9	96	1.600	96.000	0.000
ECG 10	70	1.168	70.080	0.114

This evaluation discusses the accuracy of the FFT method in analyzing ECG signals based on the results of frequency spectrum transformation. The evaluation was carried out by comparing the results obtained with reference data and measuring the level of error that occurred. In addition, interpretation of heartbeat patterns was also carried out to determine how FFT is able to accurately represent the characteristics of ECG signals. The comparison between FFT results and reference data is used as a benchmark to evaluate the error rate in frequency spectrum analysis. This process involves calculating the difference between FFT results and reference values to determine the accuracy of the method in detecting heartbeat frequencies.

The evaluation of the Fourier transform results on the ECG signal was performed by comparing the FFT results with the reference data to assess the accuracy of this method. Based on Table 2, the frequencies obtained through the FFT method were within the range corresponding to the reference heart rate frequencies, with a relatively small error rate. These results indicate that the FFT method is capable of converting ECG signals from the time domain to the frequency domain with a high degree of precision. The differences observed between the FFT results and the reference values may be attributed to factors such as the quality of the initial signal, the presence of noise, and the parameters used in the frequency analysis [25]. The error percentage shown in the table indicates that the FFT method has a sufficiently high accuracy in detecting the dominant frequency of the ECG signal. Error values ranging from 0.000% to 0.192% indicate that the difference between the FFT results and the reference data is still within acceptable limits. The main factors influencing the error are the resolution of the transformation, the length of the signal used, and the quality of the signal pre-processing before the transformation. In some cases, small differences in frequency values can also be caused by individual physiological variations that affect heartbeat patterns [26].

5. CONCLUSION

The FFT method demonstrates a high level of accuracy in detecting the main heartbeat frequency. The average error in measurements is below 0.2%, indicating that this method is reliable for biomedical signal analysis. Heart rate values calculated using the FFT method have a very small difference compared to patient data from ECG results. FFT is able to identify the main frequency peaks with high precision, thus providing results that are very close to patient data obtained from standard ECG devices.

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