IMPROVING ECG DIAGNOSIS ACCURACY THROUGH COMPUTATIONAL ANALYSIS OF P-WAVES USING DIGITIZER SOFTWARE

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Abstract. This experimental study utilized secondary data derived from ECG images representing five distinct P-wave conditions: Normal, Absent, Inverted, Left atrial enlargement, and Right atrial enlargement. The analysis of these data involved a series of six processing stages, beginning with denoising and digitization using Origin Pro Software to ensure clarity and precision of the images. Following this, both manual and automated point selection techniques were employed to extract key features for further analysis. Key metrics, including the amplitude, time, and angles for each P-wave, were then examined. These were crucial in identifying significant differences between normal and abnormal P-waves, thus contributing to a deeper understanding of the variations in the ECG patterns. In addition to these analyses, the study introduced two novel diagnostic scoring models, named after the researcher as Maaz's scoring criteria, which were based on a combination of P-wave time, amplitude, and angle measurements. These scoring models present a new and promising approach to improving the accuracy and reliability of ECG diagnostics by offering a comprehensive framework for evaluating P-wave abnormalities. The findings of this research provide valuable insights into the diagnostic process, contributing to the development of more robust and reliable methods for detecting abnormal P-wave patterns and advancing the overall field of electrocardiography.
Keywords: *electrocardiography, diagnosis, data display, data accuracy, analysis*

Introduction

Cardiovascular diseases (CVDs) are the leading cause of death globally. An estimated 17.9 million people died from CVDs in 2019, representing 32% of all global deaths. Of these deaths, 85% were due to heart attack and stroke (WHO, 2021). There are different tests used in cardiology for evaluation different pathologies. These are classified into non-invasive and invasive coronary tests. Non-invasive tests include a resting ECG, chest x-ray, and/or serum biomarkers such as cardiac troponins which help identify early signs of heart damage or underlying conditions. In some cases, further diagnostic procedures may be required to obtain more detailed information about a patient's heart health (Skelly et al., 2016). Invasive tests include echocardiography, coronary angiography, myocardial perfusion imaging via nuclear scintigraphy, magnetic resonance imaging (MRI), and computed tomography (CT) (Rehman et al., 2017). The most common non-invasive test used in cardiology for the purpose of diagnosis is the electrocardiogram test (ECG or EKG) (Arif et al., 2021). Analysis and interpretation of the ECG often perform by professional doctors, which largely depends on the doctor's training, certifications experience and knowledge. However, even experts cannot get enough information from the ECG signal. Inexperienced clinicians ordering ECGs may fail to notice interpretation errors and accept the computerized diagnosis without question (Schläpfer and Wellens, 2017). Automated diagnostic systems are increasingly crucial in diagnosing heart disease, transitioning from selecting effective lesion features for doctors to independent decision-making. ECG features, unique information

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extracted from ECG signals, represent the heart's state, enhancing the diagnostic process. The rapid advancement of machine learning methods has significantly enhanced the efficiency and intelligence of ECG analysis, enabling the use of morphological, wavelet, and statistical features in diagnostics, thereby enhancing the overall medical signal analysis process. Wearable medical devices in healthcare can potentially replace 12-lead ECG acquisition devices, detecting common cardiovascular diseases like atrial fibrillation, arrhythmia, and stress. Recent reviews on ECG analysis have predominantly focused on individual processing techniques, such as ECG pre-processing, noise reduction, and feature engineering, to improve the clarity and quality of the data before analysis. However, there is a growing interest in integrating advanced machine learning approaches to enhance the interpretation of ECG signals. Liping et al. conducted a study on various classifier algorithms used in ECG analysis, examining techniques such as Support Vector Machines (SVM), Random Forest, Bayesian Networks, and Neural Networks. These algorithms are used to classify ECG signals, identify patterns, and detect abnormalities with higher accuracy, providing valuable insights into the diagnosis and management of cardiovascular diseases. By combining these advanced algorithms with wearable devices, the potential for personalized, remote cardiovascular care is becoming increasingly viable (Xie et al., 2020).

The segments of ECG signal were divided into sub-classes, which can be utilized in tools supported by Computer Aided Design. It diminishes the time spent via cardiologists on the examination of these records. A powerful ECG heart beat grouping by incorporating five imperative modules such modules are Pre-processing, Feature extraction, Feature Selection, Clustering and Classification (Balaji and Marimuthu, 2018).

Materials and Methods

It was an experimental study. The data used was secondary and selected 3 samples each of 5 different cases i.e., Normal P-waves, Absent P-waves, Inverted P-waves, Left atrial enlargement P-waves and Right atrial enlargement P-waves. The ECG image of these P-waves passed through 6 steps. The image is first denoised to improve the quality of the image. The image is then imported into Origin Pro Software Digitizer. The start and end points are selected on the digitized image and the scale is set. Digitizer is used to manually set the points or using the scan pints using grid to automatically set the points. The digitized data is used to get the data from the points according to the scale. The data points are plotted to get the graph. The pin-point amplitude of P-waves (mV) and time (seconds) were noted at regular intervals (*Figure 1*). The time, amplitude, points on P-wave and the and the angles were calculated of all the P-waves (*Figure 2*). All the data obtained from the ECG images were compared via Origin Pro Software. All the data was then compared and analyzed to observe better predictive patterns for ECG diagnostics among the P-waves of the 5 cases.

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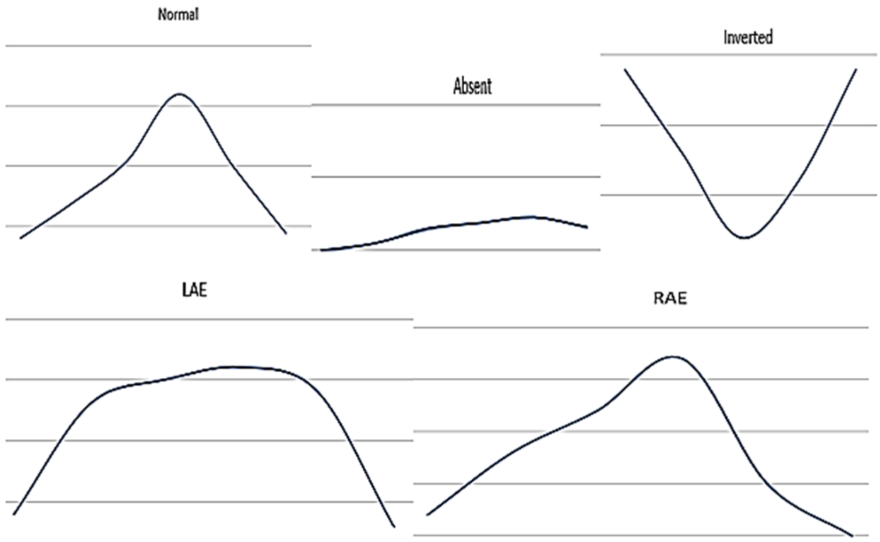

Figure 1. *Reconstruction of the P-waves for 5 cases using average Amplitude (mV) in Time (s).*

Results and Discussion

The points on the P-wave for the 5 cases were calculated at regular intervals with respect to time and amplitude and given in *Table 1*. A reconstruction of the averages of all the P-waves are shown in *Figure 1*. The measured angles and gradient % of P-waves from point zero to apex and from apex to zero for the 5 cases are shown in *Table 2* and *Table 3*. The final result for the conducted study is shown in *Table 4* with two models for new diagnostic criteria.

Table 1. *P-wave points in Time (s) and Amplitude (mV).*

Type of P-wave	Time (s)	Amplitude (mV)
Normal	0.00-0.02	0.045
	0.02-0.04	0.073
	0.04-0.06	0.104
	0.06-0.08	0.167 (Apex)
	0.08-0.10	0.105
	0.10-0.12	0.045
Absent	0.00-0.02	0.005
	0.02-0.04	0.015
	0.04-0.06	0.019
	0.06-0.08	0.023
	0.08-0.10	0.016
	0.10-0.12	N/A
Inverted	0.00-0.02	-0.056
	0.02-0.04	-0.120
	0.04-0.06	-0.179 (Apex)
	0.06-0.08	-0.142
	0.08-0.10	-0.055
	0.10-0.12	NA
Left atrial enlargement	0.00-0.02	0.088
	0.02-0.04	0.180

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	0.04-0.06	0.199
	0.06-0.08	0.206 (Apex)
	0.08-0.10	0.190
	0.10-0.12	0.081
Right atrial enlargement	0.00-0.02	0.069
	0.02-0.04	0.130
	0.04-0.06	0.174
	0.06-0.08	0.218 (Apex)
	0.08-0.10	0.105
	0.10-0.12	0.051

***Table 2**. Averages of measured angles and gradient % of P-waves from point zero to apex.*

Type of P-Wave	Initial Angle ∠P(i) (Degrees)	Initial Gradient % ⊿P(i)	Middle angle ∠P(m) (Degrees)	Middle Gradient % ⊿P(m)	Apex Angle ∠P(a) (Degrees)	Apex Gradient % ⊿P(a)
Normal	58	1.60	56	1.48	48	1.11
Absent	14	0.25	5	0.09	6	0.11
Inverted	-62	-1.88	-64	-2.05	-65	-2.15
LAE	58	1.60	71	2.90	69	2.61
RAE	55	1.43	62	1.88	58	1.60

***Table 3**. Averages of measured angles and gradient % of P-waves from point of -apex to zero.*

Type of P-Wave	Initial Angle ∠P(i) (Degrees)	Initial Gradient % ⊿P(i)	Middle angle ∠P(m) (Degrees)	Middle Gradient % ⊿P(m)	Apex Angle ∠P(a) (Degrees)	Apex Gradient % ⊿P(a)
Normal	-50	-1.19	-66	-2.25	-67	-2.36
Absent	-14	-0.25	-5	-0.09	-6	-0.11
Inverted	59	1.66	66	2.25	65	2.15
LAE	-42	-0.90	-64	-2.05	-67	-2.36
RAE	-55	-1.43	-60	-1.73	-60	-1.73

***Table 4**. Final result for establishing criteria.*

A	B	C	D	E	F	G	H	I	J
Normal	0.80-0.12	.167±.05 =.11to.22	.90±.05=.04to0.14	40 to 70 (Avg. 58)	40 to 70 (Avg. 56)	30 to 60 (Avg. 48)	-40 to -70 (Avg. -51)	-40 to -70 (Avg. -59)	-40 to -70 (Avg. -62)
Absent	0.80-0.12	.023±.01 =≤.03	.015±.01=≤.03	0 to 30 (Avg. 11)	-10 to 20 (Avg. 5)	-10 to 20 (Avg. 6)	0 to 30 (Avg. 11)	-10 to 20 (Avg. 5)	-10 to 20 (Avg. 6)
Inverted	0.80-0.12	-.179±.05 =-.12to-.23	-.110±.05=-.06to-.16	-50 to -80 (Avg. -62)	-50 to -80 (Avg. -64)	-50 to -80 (Avg. -65)	40 to 70 (Avg. 59)	50 to 80 (Avg. 66)	50 to 80 (Avg. 65)
LAE	>0.12	.206±.06 =≥.14	.157±.06=.09to.22	40 to 70 (Avg. 58)	60 to 90 (Avg. 71)	50 to 80 (Avg. 69)	-30 to -60 (Avg. -42)	-50 to -80 (Avg. -64)	-50 to -80 (Avg. -67)
RAE	0.80-0.12	.218±.06 =≥.15	.125±.06=.06to.19	40 to 70 (Avg. 55)	50 to 80 (Avg. 62)	40 to 70 (Avg. 58)	40 to 70 (Avg. -55)	-50 to -80 (Avg. -60)	-50 to -80 (Avg. -60)

Note: A=Type of P-wave; B=P-wave time; C=P-wave amplitude (mean statistic & range); D=P-wave amplitude (mean statistic & range); E=Range for initial angle 0 to ∠Pα (Degrees); F=Range for Middle angle 0 to ∠Pβ (Degrees); G=Range for Apex Angle 0 to ∠Pγ (Degrees); H=Range for -Initial Angle -∠Pα to 0 (Degrees); I=Range for -Middle Angle -∠Pα to 0 (Degrees); J=Range for -Apex Angle -∠Pα to 0 (Degrees); 5 scoring criteria=B,C,D,G,J; 9 scoring criteria=B to J.

Model 1: Diagnostic scoring for ECG diagnosis based on 5 criteria

The five (5) criteria include P-wave time, P-Wave amplitude, P-wave points (Mean statistic & Range), angle from initial to apex and Angle from apex to initial (*Table 5*) (*Figure 2*). If a P-wave has an interval of 0.12 seconds, amplitude of 18, average of P-

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points as 10, apex angle of 76 and -apex angle of 70. It means the maximum criteria fulfilled according to greatest common factor are Right atrial enlargement (RAE) with 4/5 and it shall be the final diagnosis according to algorithm.

Table 5. *Maaz's scoring criteria for ECG diagnosis.*

No of criteria met	No. of criteria not met	Broader diagnosis	Specific diagnosis
5	0	100% to Diagnosis	Positive (+) Diagnosis
4	1	80% to Diagnosis	Positive (+) Diagnosis
3	2	60% to Diagnosis	Positive (+) Diagnosis
2	3	40 % to Diagnosis	Negative (-) Diagnosis
1	4	20% to Diagnosis	Negative (-) Diagnosis
0	5	0% to Diagnosis	Negative (-) Diagnosis

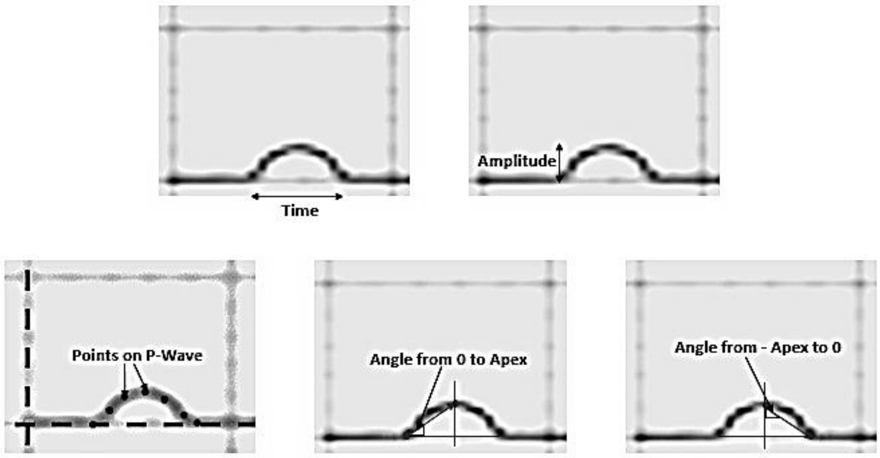

Figure 2. *Maaz's ECG diagnosis based on 5 criteria.*

Model 2: Diagnostic scoring for ECG diagnosis based on 9 criteria

The nine (9) criteria include P-wave time, P-Wave amplitude, P-wave points (Mean statistic & Range), Angle from initial to apex and Angle from apex to initial (*Table 6*) (*Figure 3*). If a P-wave has an interval of 0.90 seconds, amplitude of 22, average of P-points as 18, initial angle of 55, middle angle of 54, apex angle of 54, -initial angle of -60, -middle angle of 58 and -apex angle of 58. It means the maximum criteria fulfilled is normal with 9/9 and it shall be the final diagnosis according to algorithm.

Table 6. *Maaz's scoring criteria for ECG diagnosis.*

No of criteria met	No. of criteria not met	Broader diagnosis	Specific diagnosis
9	0	100% to Diagnosis	Positive (+) Diagnosis
8	1	89% to Diagnosis	Positive (+) Diagnosis
7	2	78% to Diagnosis	Positive (+) Diagnosis
6	3	67 % to Diagnosis	Positive (+) Diagnosis
5	4	56% to Diagnosis	Positive (+) Diagnosis
4	5	44% to Diagnosis	Negative (-) Diagnosis
3	6	33% to Diagnosis	Negative (-) Diagnosis
2	7	22% to Diagnosis	Negative (-) Diagnosis
1	8	11% to Diagnosis	Negative (-) Diagnosis
0	9	0% to Diagnosis	Negative (-) Diagnosis

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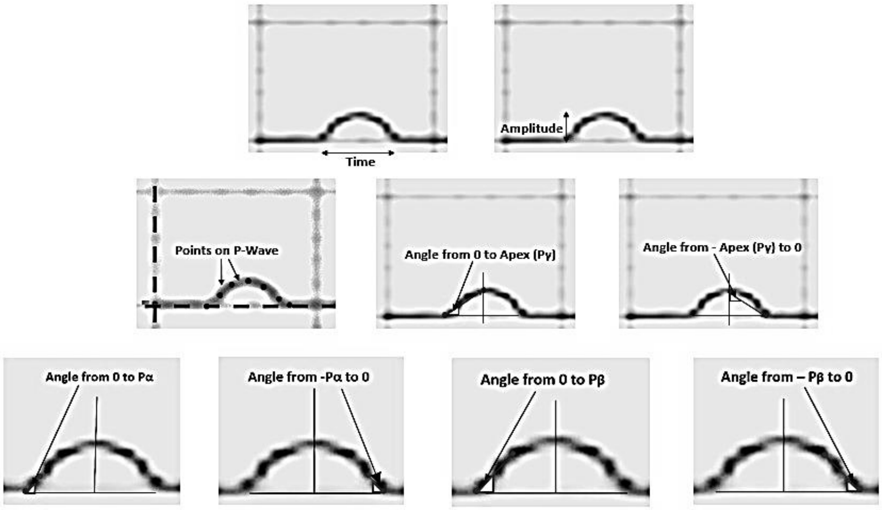

Figure 3. *Maaz's ECG diagnosis based on 9 criteria.*

Current research and developments in ECG diagnosis are focusing on several key areas, including detecting and identifying beat waves, noise filtration, and the enhancement of graphical software interfaces. Beat wave identification is crucial for accurate arrhythmia detection, while noise filtration techniques help eliminate artifacts that can distort the ECG signal, leading to clearer results. Additionally, improvements in wave identification and wave processing are essential for better characterizing complex heart rhythms and understanding underlying pathologies. Another area of focus is the development of advanced modeling techniques, which simulate the heart's electrical activity and allow for more accurate predictions and diagnoses. With the integration of machine learning and artificial intelligence, ECG analysis has become more automated, allowing for faster processing and real-time interpretation. Machine learning models can analyze large sets of ECG data to detect patterns, classify heart conditions, and predict outcomes with remarkable accuracy. Machine learning, including deep learning, has proven to be effective tools for assisting doctors with patient screening and risk assessment activities. However, they do not explain the physiological basis of classification results. Computational modeling and simulation can help in the interpretation and comprehension of important physiologically significant ECG biomarkers collected using machine learning approaches (Mincholé et al., 2019) .Automated analysis and ECG interpretation algorithms are continually refined to provide cardiologists with more reliable, consistent results, ultimately contributing to improved diagnostic criteria for ECG pathologies and better patient care. These ongoing innovations in ECG technology are paving the way for more precise, efficient, and accessible cardiovascular disease management (Mondelo et al., 2024; Monedero, 2022).

Over the last 30 years, the usage of automated ECG analysis in health care has risen dramatically. The ECG analysis is conducted by sequentially examining the heart's electrical impulses. An ECG signal consists mostly of a P wave, a QRS complex, and a T wave. The amplitude, direction, and duration of the waves, as well as their morphological characteristics, are examined. The collected data is also used to detect and diagnose normal and abnormal heart rhythms. There are several variations and combinations of ECG features or parameters that must be monitored, investigated, evaluated, and correlated. Each waveform has a unique sensitivity and specificity for detecting specific abnormalities, which can be modified by a variety of clinical and pathophysiological conditions. The same ECG pattern can be observed in people with various structural and pathophysiological conditions (Oweis and Hijazi, 2006). Computational approaches, specifically machine learning and computational modeling, are powerful tools for classification, clustering, and simulation, and they have lately been used to analyze medical data, particularly ECG data. A study described the computational approaches used for ECG analysis, with a focus on machine learning and computer simulations, as well as their accuracy, clinical consequences, and contributions to medical progress (Lyon et al., 2018).

The present study aimed to pave the way for the true identification of more accurate ECG diagnostic criteria by utilizing Maaz's current models, which focus on five and nine diagnostic criteria of P-waves. These models are designed to enhance the precision and reliability of ECG analysis by improving the characterization of P-wave morphology. By refining the P-wave classification process, the study sought to contribute to more standardized and robust ECG interpretations. Deficiencies include variability among population which may affect the quality of ECG data leading to discrepancies in published performance results of an algorithm and its performance in clinical practice (Chung et al., 2022). Limitations in the current study include limited sample size and translating these models into actual results through the integration of machine learning and showing fast application of these criteria into new ECG machines.

Conclusion

In conclusion, this experimental study employed secondary data from ECG images representing five different P-wave cases (Normal, Absent, Inverted, Left atrial enlargement, and Right atrial enlargement). The data underwent six processing steps, starting with denoising and digitization using Origin Pro Software, followed by manual and automated point selection. Key metrics such as the amplitude, time, and angle for each P-wave were analyzed using Origin Pro Software to identify significant differences between normal and abnormal P-waves. The study introduced two diagnostic scoring models based on different criteria named after the researcher as Maaz’s scoring criteria, including P-wave time, amplitude, and angle measurements, offering a new approach to improving ECG diagnostics. The findings contribute to the development of more accurate and reliable methods for diagnosing abnormal P-wave patterns.

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Conflict of interest

The authors confirm that there is no conflict of interest involve with any parties in this research study.

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