IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 16 May 2025, accepted 9 June 2025, date of publication 12 June 2025, date of current version 23 June 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3579256

RESEARCH ARTICLE

Wearable System for Cardiac Diagnosis and Monitoring: Clustering Analysis and Usability Assessment Using Fractal Geometry

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This work was supported in part by the Project "Cardiac Diagnosis and Monitoring Using a Physical-Mathematical Methodology Based on Fractal Geometry and Dynamic Systems Incorporated in Wearable Technologies" Applied Research Projects 2022-2 through PROCIENCIA CONCYTEC under Grant PE501080050-2022.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Comité Institucional de Ética de la Investigación UCSM under Application No. 042-2023.

ABSTRACT Heart rate abnormalities, including tachycardia and bradycardia, are among the leading global causes of morbidity, necessitating continuous and accurate monitoring for early detection and intervention. This study introduces an innovative smartwatch-based cardiac monitoring system that integrates fractal geometry analysis, dynamical systems modeling, and clustering techniques to enhance diagnostic precision. Unlike conventional smartwatch-based monitoring systems, this approach employs advanced mathematical modeling to identify nonlinear patterns in heart rate dynamics, enabling more precise differentiation between normal and pathological conditions. The system was developed using the CRISP-DM methodology, ensuring a structured and data-driven implementation. A mobile application, "My Cardio," was designed for Android-based smartwatches, enabling the collection of real-time heart rate data and cloud storage for subsequent fractal-based processing. Additionally, a clustering analysis was performed on data from patients with and without cardiac history, identifying three distinct patient groups based on heart rate characteristics. Cluster 0 included individuals with lower, stable heart rates; Cluster 1 represented intermediate variations; and Cluster 2 comprised patients with significantly elevated heart rates associated with higher clinical risk. The findings were statistically validated and visualized, demonstrating that integrating clustering techniques with fractal geometry enhances the detection of clinically relevant cardiac patterns. Furthermore, a usability assessment using the System Usability Scale (SUS) yielded a score of 80.3 or higher, confirming high user acceptance and feasibility for widespread adoption. This study differentiates itself from existing approaches by combining wearable technology with advanced computational techniques to enhance cardiac diagnosis and monitoring. The results underscore the potential of smartwatch-based systems as a noninvasive, intelligent alternative for continuous cardiovascular assessment, paving the way for future applications in digital cardiology and telemedicine.

INDEX TERMS Clustering, fractal geometry, cardiac monitoring, smartwatch, usability.

I. INTRODUCTION

Cardiovascular diseases (CVD) represent one of the leading causes of mortality globally, being responsible for

The associate editor coordinating the review of this manuscript and approving it for publication was Norbert Herencsar.

approximately 45% of all deaths in Europe and 37% in the Central Asia region, according to data from the World Health Organization (WHO). These conditions include a variety of disorders, such as coronary heart disease, stroke, and rheumatic heart disease, which significantly affect both the quality of life of patients and public health systems [1]. In Peru, the burden of cardiovascular diseases is alarming, with the Pan American Health Organization (PAHO) reporting 73.5 deaths per 100,000 inhabitants in 2019, placing the country among the lowest quintile in global rankings [2].

Continuous and noninvasive cardiac activity monitoring has emerged as a crucial tool, highlighting the role of wearable technologies such as smartwatches. These devices enable the real-time recording of relevant heart rate data, revolutionizing access to critical clinical information.

In that sense, to improve the precision and effectiveness of cardiac monitoring, new and diverse approaches have been introduced, such as those based on dynamic systems and fractal geometry. The theory of dynamic systems has given rise to new possibilities for diagnosing these pathologies in patients through nonlinear techniques that capture the nature of cardiovascular behavior. For example, this theoretical framework has facilitated the analysis of heart rate through innovative methods and perspectives, offering new insights into its patterns and variability in the context of cardiac function. On the other hand, Fractal geometry enables the measurement of irregularities in heart rate patterns, offering more profound insights into physiological processes that are initially imperceptible. Leveraging these mathematical tools, researchers strive to enhance the detection of pathological patterns that may elude traditional diagnostic methods utilized by healthcare professionals [3].

In parallel, wearable technologies have emerged as viable alternatives to conventional monitoring devices, such as Holter monitors, which, although practical, can be uncomfortable and may not always detect intermittent arrhythmias due to their exploratory nature [4]. While smartwatches have shown potential for detecting problems such as atrial fibrillation, questions remain about their acceptance and clinical utility, particularly in populations at higher cardiovascular risk, such as the elderly [5]. Nonetheless, recent studies have demonstrated the feasibility and usability of smartwatch-based cardiac monitoring systems, reinforcing their role in the early detection of heart irregularities.

Clustering analysis has emerged as a powerful technique in biomedical signal processing, allowing the identification of distinct patient groups based on cardiac behavior. By applying clustering methods such as k-means, researchers can automatically classify heartbeat patterns, detect anomalies, and improve the accuracy of arrhythmia detection in electrocardiogram (ECG) data [6].

In this study, we propose a novel wearable cardiac diagnosis and monitoring system that integrates smartwatch-based data collection with clustering analysis and fractal geometry for advanced cardiac assessment. This system is implemented through a mobile application called "My Cardio," developed for Android-based smartwatches following the CRISP-DM methodology. The application captures heart rate data, stores it in the cloud, and applies fractal analysis and clustering techniques to classify patients into three groups based on heart rate characteristics. Furthermore, usability assessment was conducted using the System Usability Scale (SUS), ensuring the application meets user experience expectations.

This research aims to validate the viability of smartwatch-based cardiac monitoring, demonstrating its potential to enhance diagnosis, improve usability, and establish wearable technologies as key tools in modern cardiology. This study contributes to the advancement of intelligent, non-invasive cardiac monitoring solutions by integrating clustering, fractal geometry, and smartwatch technology.

II. LITERATURE REVIEW

Arrhythmia detection is a well-developed topic in the literature. For example, the study by Szep et al. [7] designed a continuous cardiac monitoring system that leverages modern portable devices to detect arrhythmias and predict potentially dangerous ones several minutes in advance. This proposal utilizes a single machine learning algorithm, where the model is trained on ECG data from the PhysioNet 2015 dataset. While it proposes real-time monitoring, it does not utilize data from wearable devices or conduct validation experiments using patient clinical data. This aspect is crucial for our study, and we propose validating it using patient data collected from wearable devices.

Cardiovascular health is a topic of interest to the scientific community; therefore, the team of Benziger et al. [8] found low prevalences of adequate cardiovascular health in Peru. Uncommonly, few participants met all the ideal cardiovascular health metrics, and only 10% reached the expected metrics. Complementing the above information, it was also found that participants in the lowest socioeconomic tercile were more likely to have deficiencies in cardiovascular health, unlike those with medium and high socioeconomic status; these results persisted even after adjusting for sex, age, and educational level. In addition to this, studies have found that not only is the adult population affected, but it has been shown that Peruvian adolescents also have a high prevalence of risk factors for developing cardiovascular diseases in the future [9]. This reflects the severity and significance of the disease in Peru, which aligns with global statistics.

Regarding dynamic systems, Rodríguez et al. [10] applied dynamic systems and fractal geometry in the diagnostic evaluation of continuous Holter recordings, successfully differentiating normality and abnormality. Likewise, Rodriguez et al. [11] performed an ECG analysis on a database of ECG signals using the fractal R/S algorithm transformation. They established their graphical approach to the pre-diagnosis of arrhythmias based on statistical parameters of confidence intervals. The results confirm the fractal graphic approach as a reliable preliminary stage for pre-diagnosis, with several critical applications in public health. These findings are crucial for our study, as they demonstrate the validity of utilizing dynamical systems and fractal geometry for early diagnosis. However, Holter recordings cannot be used for real-time diagnostic and monitoring processes; our study proposes using smartwatches that use real-time heart rate data.

Smart watches, wearable devices connected via short-range wireless networks, have transformed health monitoring by integrating specific heart rate monitoring applications. Diodato et al. [12] noted that these devices have proven to be reliable tools for detecting atrial fibrillation using optical sensors, enabling preventive interventions in potentially fatal complications. This study is essential for our proposal because it validates the use of smartwatches in monitoring heart disease. Other studies provide further support for our proposal, as described below:

Touiti et al. [13] emphasize that health functionalities in wearable devices are ensured by built-in sensors capable of recording single-lead electrocardiograms. Although less accurate than 12-lead ECGs, these devices are considered a compelling solution for detecting cardiac rhythm disorders and documenting electrical symptoms.

Smartwatches are reliable in capturing heart rate data and data on associated risk factors. Physical inactivity is a modifiable cardiovascular risk factor, and Martinato et al. [14] validated the accuracy of wearable devices in quantifying physical activity. Their study concludes that these devices are reliable tools in real-life settings, although not in a medical context.

In the work of Han et al. [15] They designed a photoplethysmographic spike detection (PPG) algorithm that automatically detects and discriminates various heart rhythms: normal sinus rhythms (NSR), premature atrial contraction (PAC), premature ventricular contraction (PVC), and atrial fibrillation (AF) for PPG signals collected from a smartwatch, accurately estimating heart rates (HRs) among various arrhythmias, which improves the accuracy of AF detection. While this study does not propose a diagnostic or monitoring system, it validates the use of photoplethysmographic (PPG) spikes in heart rhythm detection. Our study utilizes explicit photoplethysmographic (PPG) spikes to capture heart rate using smartwatches.

Using smartwatch software in disease detection is not a new topic. Thus, Sengupta et al. [16] explored the usability of mHealth systems, such as Heartbeat, specifically designed for users with cardiovascular diseases. With an average system usability score of 83.60, these systems have shown acceptability and effectiveness in improving health behaviors. This study primarily focused on demonstrating acceptability while deemphasizing the demonstration of reliability in a clinical setting. This aspect is essential, and we take this gap into account.

Studies like those by Mikhail et al. [17] have reviewed research highlighting the diagnostic efficacy and usability of smartwatches, particularly among older adults. Software such as Pulsewatch facilitates the detection of atrial fibrillation through a simplified interface, addressing cognitive and technological barriers. These studies propose using software in smartwatches, but they only detect atrial fibrillation and not arrhythmia specifically, which is the subject of our research.

The most recent studies utilize artificial intelligence in their proposals. Several studies, including those by Caillol et al. [18], Leroux et al. [19], and Rajakariar et al. [20], have investigated the detection of arrhythmias using artificial intelligence and data from wearable devices, such as smartwatches.

Our work examines the most significant proposals for detecting arrhythmia using wearable devices, such as smartwatches. Therefore, the work most closely related to our proposal integrates smartwatches, smartwatch software, artificial intelligence, and heart rate data. Thus, in the study of Huillcen Baca et al. [21], proposals for detecting arrhythmias using artificial intelligence and smartwatch data were reviewed, such as Caillol et al. [18], Ploux et al. [22], Abu-Alrub et al. [23], Han et al. [24], and Racine et al. [25]. These studies validate their proposals with accuracy metrics, specificity, and sensitivity, which are the foundations for clinical diagnosis. However, they all use ECGs as arrhythmia detection data; it has been proven that smartwatches still lack the accuracy of a Holter monitor in capturing ECG data. Thus, our proposal utilizes heart rate data as a source of information for arrhythmia detection.

Integrating these perspectives, the present study also incorporates a statistical clustering analysis to identify patterns in heart rate data. As highlighted by recent studies [26], clustering algorithms have proven to be practical tools for classifying patients based on multivariate data, facilitating the differentiation between groups with high cardiovascular risk and those with standard conditions. Furthermore, researchers such as Kumar et al. [27] proposed a hybrid approach called Fuzz-ClustNet, which combines fuzzy clustering and deep neural networks for detecting arrhythmias from ECG signals, showing promising results in clinical settings. Similarly, Luz et al. [28] highlighted the capabilities of clustering to classify heartbeats and detect arrhythmia patterns, emphasizing its applicability to optimize diagnostic tools.

Finally, recent studies have reinforced the potential of artificial intelligence in cardiac monitoring, highlighting its real-time clinical applicability and diagnostic accuracy. For example, Yagi et al. [29] developed a deep learning-based model that predicts chemotherapy-induced cardiotoxicity using baseline electrocardiograms, achieving an AUC of 0.78 for two-year predictions, significantly improving risk stratification in cancer patients. Similarly, Jacobs et al. [30] utilized artificial intelligence to analyze ECGs and detect left ventricular dysfunction following anthracycline therapy, achieving an AUC of 0.93 for reduced ejection fraction, which outperformed traditional monitoring methods.

This recent research [31] reinforces the importance of incorporating AI-based tools not only for early prediction but also for personalized cardiac monitoring in high-risk patients.

Based on this literature review, it is observed that our topic is current and of interest to the scientific community. Studies have been mentioned that generally share the same objective, but are not comprehensive or lack several aspects that render their use in clinical settings and real-time applications unfeasible. Therefore, our proposal addresses these shortcomings and aims to thoroughly detect, and monitor arrhythmia based on smartwatches, smartwatch software, dynamic systems, fractal geometry, and artificial intelligence algorithms. It is based on the use of real-time heart rate data. To our knowledge, no comprehensive proposal exists that addresses all these aspects.

III. MATERIALS AND METHODS

A. POPULATION

Retrospective information was collected from 24-hour ambulatory monitoring records obtained from the databases of primary care health services, the Aliviari Clinic of the UCSM, and the 2 MINSA Hospitals in the Arequipa Region.

The cardiac status reported in the Holter records was verified by a specialist physician with expertise in the area according to established medical criteria. Additionally, this professional classified the patient records into three categories: normal, acute, and intermediate. A total of 272 records were taken, of which 193 were normal and 79 presented arrhythmias. Although the original methodology was developed for individuals over 20 years of age, this research included 7 cases between 18 and 20 years of age to evaluate whether there was any significant difference in the mathematical characteristics of this population. The inclusion and exclusion criteria are detailed below:

Inclusion criteria:

1. People of both sexes with ages above 17 years.
2. Holter recordings with at least 24 hours of continuous recording.
3. Holter recordings containing maximum and minimum heart rates and the number of beats per hour for at least 24 continuous hours
4. Holter recordings contain information on age, the reason for requesting Holter monitoring, and the specialist's diagnosis.

Exclusion criteria:

1. Holter recordings from pediatric patients or those under 18 years of age.
2. Holter recordings from people undergoing cardiovascular disease studies without diagnostic confirmation according to clinical parameters.
3. Holter recordings last less than 24 hours.
4. Incomplete Holter recordings, in terms of information on maximum and minimum heart rate and the number of beats per hour.

Additionally, 25 patient records were collected over 20 hours using the "Mi Cardio" app, which was installed on smartwatches. Of these, 13 have arrhythmia, and 12 are normal.

B. PROCEDURE

The development of the mobile App system was structured using the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology [32], which consists of six main stages: business understanding, data understanding, data processing, modeling, evaluation, and deployment. Each stage is described in detail below.

1) BUSINESS UNDERSTANDING

In this initial stage, the main problem was identified: a high incidence of fatal heart disease. The proposal aims to address this situation by developing software that enables the diagnosis of cardiac dynamics using dynamic systems and fractal geometry. Figure 1 illustrates the proposed flow of activities in the study.

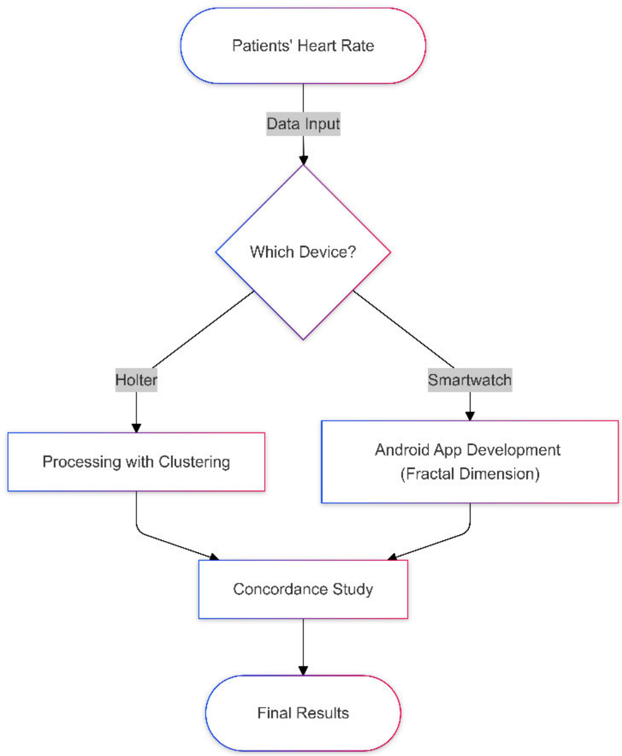

FIGURE 1. Flowchart of the cardiac monitoring system, comparingHolter-based clustering analysis and smartwatch-based fractal dimension processing.

Fractal geometry is a mathematical approach used to study complex and irregular patterns. It has been widely applied in biology and medicine, particularly in the analysis of heart behavior. In this study, we use it to examine how heart rate changes over time.

The first step is to create a delay map, a method from dynamic systems theory that transforms heart rate signals into a visual pattern. This pattern is known as an attractor, illustrating how the heart's rhythm evolves. The attractor gives us a geometric picture of the heart's behavior.

To measure how irregular the attractor is, we calculate its fractal dimension using the Box-Counting method. This involves placing grids of different sizes over the attractor and counting the number of square grids it fills. Repeating this process with various grid sizes reveals the complexity of the pattern, enabling us to identify differences between normal and abnormal heart dynamics. The fractal dimension is then computed using equation (1).

$$D = \frac{LogN_1(2^{-(k+1)}) - LogN_2(2^{-k})}{Log2^{k+1} - Log2^k} = Log_2 \frac{N_1(2^{-(k+1)})}{N_2(2^{-k})} \tag{1}$$

where:

N_1: Number of spaces occupied by the attractor in the partition grid K.

N_2: Number of spaces occupied by the attractor in the partition grid $K + 1$

K: Partition degree of grid 1.

$K + 1$: Partition degree of grid 2.

D: Fractal dimension.

In addition to calculating the fractal dimension, this study also analyzes the number of cells occupied by the attractor using two types of grids. These grids correspond to resolutions of 5 beats per minute and 10 beats per minute, and their results were identified by the parameters Kp and Kg, respectively. These two additional values complement the mathematical characterization of the cardiac signal, providing further information about the spatial distribution of cardiac behavior.

2) DATA UNDERSTANDING

The attributes to be collected were defined, such as heart rate measured through sensors in smartwatches. The Samsung Galaxy 4 model was used for this study, which offers bioactive sensors capable of recording electrocardiograms (ECG) and blood pressure in real-time after an initial calibration. Additionally, these sensors monitor heart rate and detect any abnormalities.

The dataset used consists of 272 patient records of heart rate readings collected from Holters. Additionally, 20 participants over 20 years old recorded their heart rates using a mobile app developed and installed on their smartwatches: 10 with a history of heart problems and 10 with no such history. Data, including patient ID, heart rate, capture time, and monitoring end, were recorded. The protocol complied with the recommendations of the Declaration of Helsinki and was approved by the local ethics committee.

3) DATA PROCESSING

For the manual application of the method and characterization of variables, the following steps were taken:

a: CHARACTERIZATION OF VARIABLES

For the application of the method and characterization of variables, the following steps were carried out:

a) Tabulation of the minimum and maximum heart rate and number of beats per hour.
b) Generation of numerical sequences based on the minimum and maximum frequency limits, employing a pseudo-random number generation algorithm.
c) Creation of ordered pairs from the generated sequences.
d) Graphical representation of the data using chaotic attractors.
e) Superposition of Kp (5 beats/min) and Kg (10 beats/min) grids onto the attractors.
f) Calculation of the fractal dimension through the Box-Counting method.
g) Analysis of differences between normal and abnormal states.

b: VALIDATION OF THE DIAGNOSTIC METHOD

- Evaluation of results obtained with smartwatches.
- Comparison of diagnoses using the kappa coefficient, which evaluates the agreement between two results while excluding potential concordance due to chance, using the following equation (2):

$$K = \frac{C_o - C_a}{T_o - C_a} \tag{2}$$

where: C_o: observed concordances, T_o: Total cases, C_a: Concordances by chance, according to equation (3):

$$C_a = \left[\frac{f_1 x c_1}{T_o}\right] + \left[\frac{f_2 x c_2}{T_o}\right] \tag{3}$$

where: f_1: cases with mathematical values within the limits of normality, c_1: cases diagnosed clinically within normality, f_2: cases with mathematical values associated with acute disease, c_2: cases clinically diagnosed with acute disease. T_o: total number of normal cases and cases with acute disease.

4) MODELING

The system architecture includes an application called "My Cardio," developed in Android Studio with Java. It uses Samsung Galaxy 4 sensors to capture data in 20 hours. The data collected is stored in the cloud for later analysis using fractal geometry and dynamic systems methodologies. The results are visualized through a web application to facilitate access to interested parties. Figure 2 shows the Architecture of the study proposal.

The smartwatch application was developed using Android Studio version 2023.2.1. Project setup:

- Target: Wear OS (Android 7.1+)
- Language: Java
- Required libraries: android.hardware.Sensor, SensorManager, and SensorEventListener.
- Permissions in AndroidManifest.xml: BODY_SENSORS and INTERNET

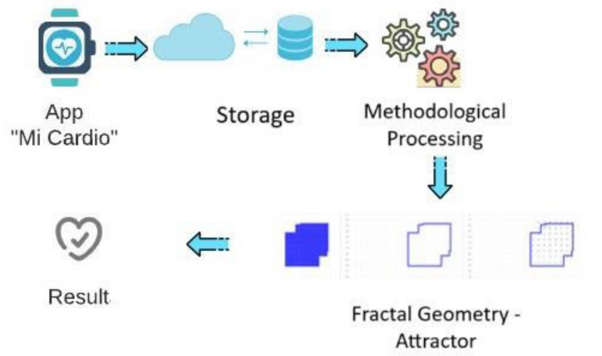

FIGURE 2. **Workflow of the "Mi Cardio" app. Heart rate data is stored in the cloud, processed using fractal geometry, and generates attractors for cardiac pattern analysis, producing diagnostic results [33].**

The minimum requirements established for the application include:

- Allow the user to view their heart rate in real-time.
- Transmit heart rate data at a rate of one second to a server.
- Record and send information about blood oxygen saturation.
- Incorporate the option to add a unique user code to facilitate data transfer.

The application was developed in accordance with the general design recommendations for healthcare applications on Wear OS devices outlined by [34]. Figure 3 presents the initial interface designed for the smartwatch.

FIGURE 3. **The initial interface was designed for the smartwatch application "MiCardio." The left image shows the app icon within the smartwatch menu, while the right displays the main interface, providing options for heart rate monitoring, alerts, and additional health metrics.**

Regarding Internet connectivity, the Samsung Galaxy Watch 4 automatically syncs with the paired mobile device using the phone's Wi-Fi connection or mobile network. To ensure the application's proper functioning, the user must grant the required permissions during installation and first use.

Figure 4 illustrates the main menu screen, which presents three available options.

FIGURE 4. **Heart Rate Menu in the "Mi Cardio" smartwatch application. The interface includes options for starting, stopping, and sending heart rate data in real-time, ensuring effective monitoring and data transmission for clinical evaluation.**

The "Pulse" option directs the user to a screen displaying the heart rate sensor reading. In this view, the heart rate is displayed in real-time, and the start and pause functions for data transmission are accessible. A user code must be entered beforehand to send information.

Once the smartwatch application has captured the heart rate data for 20 hours, it is sent to a cloud server, where it is managed through a web application organized into the following modules:

a: PATIENTS

This module allows you to view the details of all patients on a single screen. It also facilitates access to patients' heartbeat data using the smartwatch and the application. As shown in Figure 5, the samples captured by each patient can be consulted.

FIGURE 5. **Patients Module. It displays patient details, including identity, age, email, health conditions, and recorded heart rate data.**

b: ADD PATIENTS

This module is designed to register new patients, including their personal information, email address, and any previous medical conditions selected from a predefined list. The available options can be managed from the maintenance section, as illustrated in Figure 6.

c: HOLTER'S SAMPLES

The sample's view, shown in Figure 7, allows access to all samples taken by the patient. In this view, the data collected from the Holter device used in the study, along with the specific details of each sample, are displayed.

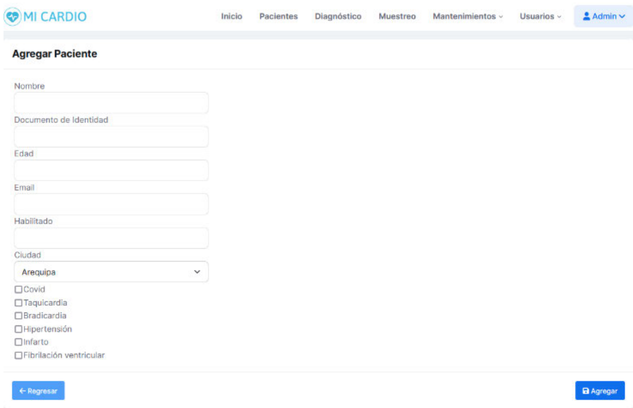

FIGURE 6. **Add Patients Module. It allows for the entry of patient details, including identity, age, email, city, and any pre-existing conditions.**

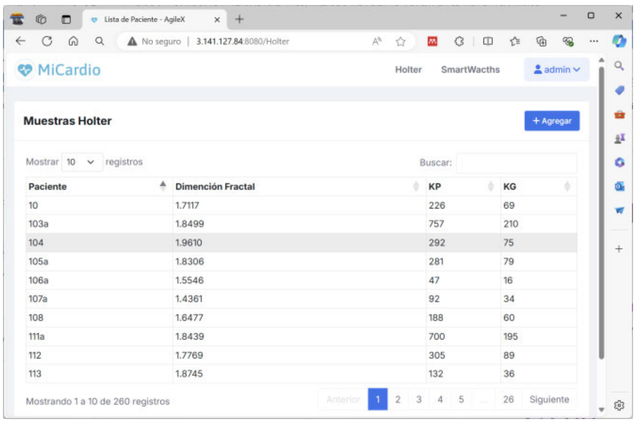

FIGURE 7. **Holter Samples Module. Enables efficient monitoring and comparison of Holter-recorded heart rate patterns.**

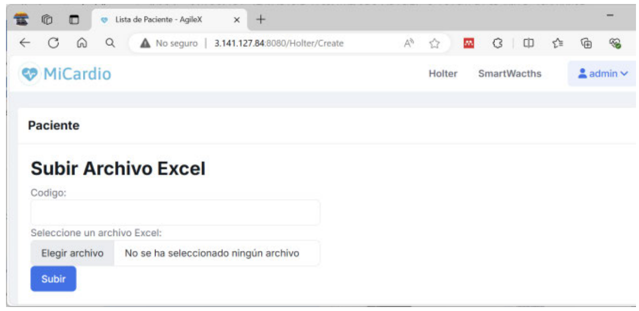

FIGURE 9. **Uploads Sample Details Module. Allows users to upload Excel files containing patient heart rate data.**

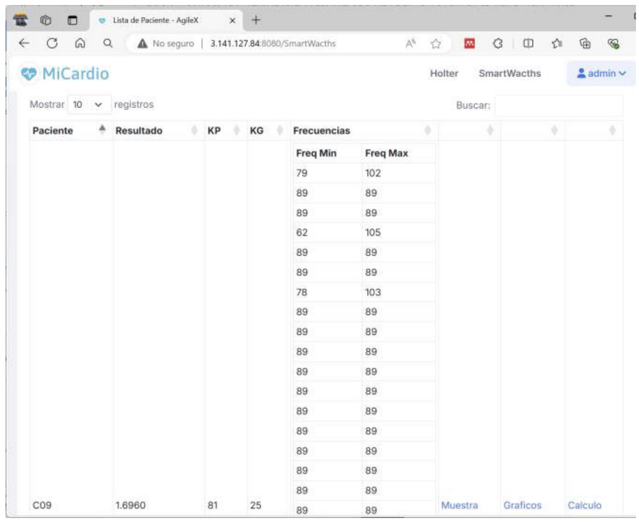

FIGURE 10. **Smartwatch Sample Module. Displays patient heart rate data, including minimum and maximum frequencies, fractal dimension results, and KP/KG parameters.**

d: SAMPLE DETAILS

This module allows the incorporation of new diagnoses based on the severity of the findings obtained during the patient study. Figure 8 illustrates its functionality and structure.

FIGURE 8. **Add the Diagnosis Module. This module facilitates the efficient documentation and management of cardiac health assessments.**

e: UPLOAD SAMPLES

The sample details contain patient information and the study response. As shown in Figure 9, an Excel file must be attached to obtain the response.

f: SMARTWATCH SAMPLES

The sample's view, shown in Figure 10, allows access to all samples taken by the patient. In this view, the data collected from the smartwatch device is displayed, along with the specific details of each sample.

g: ATTRACTOR GRAPH

Figure 11 shows the graph of the attractors resulting from each patient. For example, the fractal dimension $Df = 1.7488$ and the electrical impulse strength parameters $Kp = 447$ and $Kg = 133$ are considered.

5) CLUSTERING

The clustering analysis in this study aimed to classify patients based on heart rate variability, distinguishing between normal and pathological cardiac patterns. The methodology used consists of the following stages:

a) Selection Of Features:

The dataset used has 272 patient records of cardiac readings taken from Holters that contain the following columns:

- *Sex: Indicates the patient's sex (0 = male, 1 =* female).
- *age*: Patient's age.
- *fcavg*: Average heart rate.
- *fcmax*: Maximum heart rate.

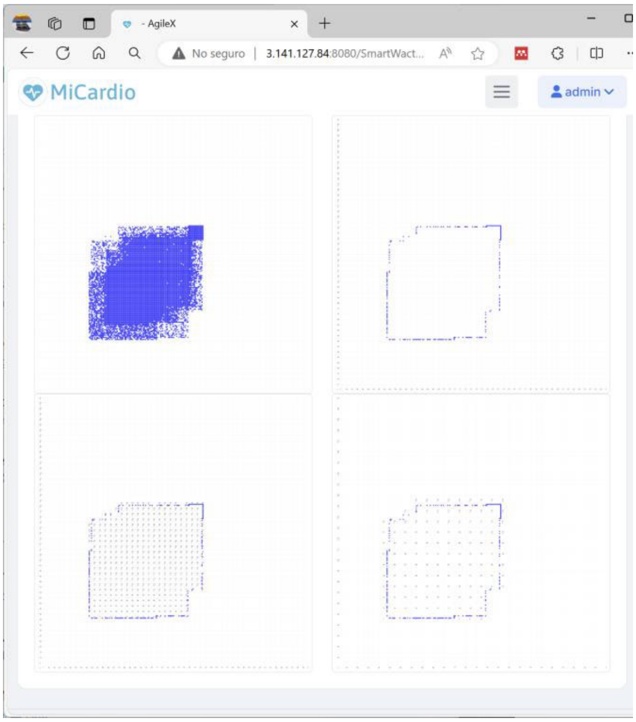

FIGURE 11. Attractor graph. Displays fractal representations of cardiac dynamics, illustrating variations in heart rate patterns through different attractor densities for advanced cardiac analysis.

- *fcmin*: Minimum heart rate.
- *dx_holter_final*: Final diagnosis based on monitoring (arrhythmia or not).

The key variables related to heart rate were selected: average heart rate (*fcavg*), maximum heart rate (*fcmax*), and minimum heart rate (*fcmin*). These features provided relevant information to group patients into meaningful categories. The selected features were normalized using the Z-score technique to ensure that the variables had a comparable scale, with a mean of zero and a standard deviation of one. This step minimized the bias caused by differences in magnitude between the features.

b) Determination Of the Optimal Number of Clusters:

The Elbow Method was used to determine the optimal number of clusters (k). This approach evaluates the sum of squared distances (inertia) within each cluster and identifies the point where adding more clusters does not significantly reduce inertia. To apply clustering, we selected the relevant numerical variables we were interested in analyzing: age, fcavg, fcmax, fcmin. Since the values for these variables are on different scales, we use StandardScaler to standardize the data. We created K-Means models for various numbers of clusters, from $k = 1$ to $k = 10$, and for each, we calculated the inertia, which represents the sum of the squared errors within the clusters. The generated elbow method generates a downward curve, where the "elbow" or inflection of this curve indicates the point at which adding more clusters no longer significantly improves data compaction. This value is considered the optimal number of clusters. Based on the analysis, $k = 3$ was selected, representing three patient groups:

1. **Cluster 0:** Patients with lower heart rate values (normal conditions).
2. **Cluster 1:** Patients with intermediate heart rate variability.
3. **Cluster 2:** Patients with high heart rate values (linked to severe cardiac conditions).

To validate the effectiveness of this choice, the Silhouette Coefficient was calculated, which measures how well separated each cluster is from the others. A higher silhouette score (>0.5) confirmed good cohesion and separation between clusters. We also used a file of new measurements captured by smartwatches where the inflection point on the curve is located, which also suggests that k = 3 is an appropriate choice, thus validating the consistency of the original model.

Moreover, a clinical interpretation was performed, confirming that the three clusters correspond to meaningful physiological profiles, ranging from healthy to potentially at-risk patients. The validation result with the Elbow method is shown in Figure 12.

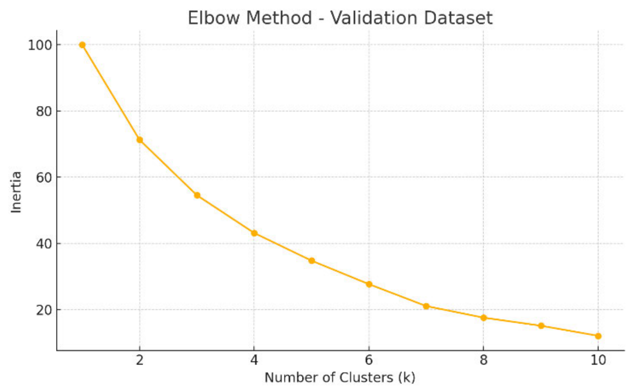

FIGURE 12. The elbow method was applied to the validation dataset. The curve again suggests that k = 3 is a good number of clusters.

C. IMPLEMENTATION OF THE K-MEANS ALGORITHM

The K-Means algorithm, widely used in biomedical signal clustering [27], was implemented using the Scikit-learn library. This algorithm iteratively assigns each data point to the closest cluster centroid and recalculates centroid positions until convergence is reached.

IV. EVALUATION AND RESULTS

A. ANALYSIS OF SOFTWARE RESULTS

The T-Student statistical test was used to analyze results, which is suitable for comparing numerical data under the assumption that they follow a normal distribution. The objective of the analysis was to determine whether there are significant differences between the means of the two groups evaluated: "Cardio" and "Healthy."

Table 1 presents the values generated after processing the data using the physical-mathematical method and fractal geometry for each group:

TABLE 1. Results of the physical-mathematical and fractal geometry process.

Num.	Condition-Group1	Values	Condition-Group2	Values
1	Cardio	1.8138	Healthy	1.8334
2	Cardio	1.7489	Healthy	1.4657
3	Cardio	1.9109	Healthy	1.8174
4	Cardio	1.6398	Healthy	1.8911
5	Cardio	1.9511	Healthy	1.8592
6	Cardio	1.6960	Healthy	1.9839
7	Cardio	1.6663	Healthy	1.7738
8	Cardio	1.7489	Healthy	1.7327
9	Cardio	1.8138	Healthy	1.7442
10	Cardio	1.7561	Healthy	1.7862
11	Cardio	1.8518	Healthy	1.6960
12	Cardio	1.8520	Healthy	1.7345
13	Cardio	1.8145		

For this analysis, the following hypotheses were established:

H_0: There are no significant differences between the meanings of the two groups.

H_1: There are significant differences between the meanings of the two groups.

The Excel tool was used to run the T-Student test. The results obtained after its application are shown in Table 2.

TABLE 2. Hypothesis test results.

	Variable 1 (Cardio)	*Variable 2 (Healthy)*
Mean	1.7895	1.7765
Variance	0.0084	0.0159
Observations	13	12
Pooled variance	0.0120	
Hypothesized difference of means	0	
Degrees of freedom	23	
t-statistic	**0.2926**	
P(T<=t) one-tailed	0.3864	
Critical value of *t* (one-tailed)	1.7138	
P(T<=t) two-tailed	**0.7728**	
Critical value of t (two-tailed)	2.0686	

The average values of each group are close, suggesting no significant differences between them on average.

The Cardio group has a lower variance, indicating that its values are more concentrated around the mean, whereas the Healthy group exhibits greater dispersion.

The pooled variance (0.0120) is calculated to estimate the average variability of the two groups. It is useful when the groups' variances are assumed equal, making the t-test easier to calculate.

Hypothesized difference of meaning (0). This represents the null hypothesis ($H0$), which assumes no difference between the group means.

The degrees of freedom (23) are calculated based on the sample size and are used to determine the critical values for the t-test. The t-statistic (0.2926) measures the magnitude of the difference relative to the data's variability. A low value suggests that the differences between the means are not significant.

Since the p-value obtained was more significant than 0.05 (0.7728), the alternative hypothesis was rejected, and the null hypothesis was not accepted. This suggests that there are no significant differences in the meanings between the two groups analyzed, "Cardio" and "Healthy."

Regarding usability, the Systems Usability Scale (SUS) [4] was used to evaluate the smartwatch application with 20 users. This scale consists of 10 predefined and validated questions.

The results were based on a Likert scale, where 1 represented "totally disagree" and 5 represented "totally agree." The results are shown in Table 3:

TABLE 3. Usability results summary(SUS).

Pregunta	Interpretation of the Mean
1. I think I would like to use this system frequently.	Most users strongly agreed (5). This reflects a high intention to use frequently.
2. I found the system unnecessarily complex.	Responses were concentrated on "Strongly Disagree" (1), indicating that the system is easy to use.
3. I thought the system was easy to use.	Positive responses predominated (4-5), confirming a high perception of ease of use.
4. I think I would need support from a technician to use this system.	Most respondents chose "Strongly Disagree" (1), indicating a lack of confidence in using the independent system.
5. I found the various functions to be well integrated.	The predominant acceptance (4-5) suggests that the system's functionalities are well designed
6. I thought there were too many inconsistencies in this system.	Most selected "Strongly Disagree" (1), indicating consistency in design and operation.
7. I imagine most people would learn to use this system quickly.	High positive responses (4-5), evidencing a short learning curve for potential users.
8. I found the system very complicated to use.	"Strongly Disagree" (1) was the predominant response, confirming the system's simplicity.
9. I felt very confident using the system.	Most respondents (4-5) responded positively, indicating high confidence in using the system.
10. I needed to learn a lot of things before I could start with this system.	The dominant response was "Strongly Disagreed" (1), reflecting an intuitive and accessible design.

The results indicate a score above 80.3, which classifies the usability experience as "Good" according to the SUS scale standards. The system is perceived as easy to use, consistent, and reliable, featuring an intuitive design that enables its use without requiring technical support. This reinforces the application's acceptability as a practical tool for monitoring heart rate through the smartwatch.

B. ANALYSIS OF CLUSTERING RESULTS

The identified clusters were visualized in a two-dimensional space by dimensionality reduction, using techniques such as t-SNE to illustrate the separation between groups.

Each cluster was analyzed in terms of its average features (minimum, maximum, and average heart rate), which allowed the interpretation of each group's specific patterns and their relationship to clinical conditions.

The silhouette coefficient, whose positive values indicated good internal cohesion and separation between clusters, assessed the quality of the clustering.

The centroids of each cluster were interpreted as representing the average characteristics of the patients in that group.

Figure 13 shows the result of the Cluster Visualization analysis (PCA-Reduced features)

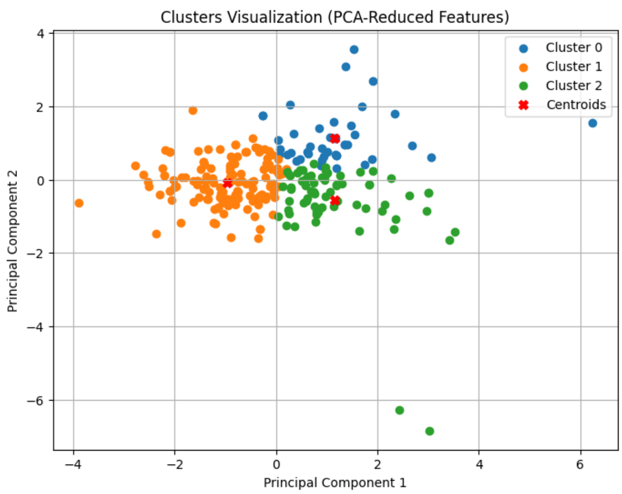

FIGURE 13. Cluster Visualization (PCA-Reduced features).

It can be inferred from the results shown in Table 4 how the original variables (*fcavg*, *fcmax*, *fcmin*) contribute to the principal components.

TABLE 4. Results of the main components.

	fcavg	*fcmax*	*fcmin*
Principal Component 1	0.697018	0.479011	0.533587
Principal Component 2	-0.006886	0.748575	-0.663014

1) PRINCIPAL COMPONENT 1 (PC1)

- *fcavg*: 0.697 (Predominant contribution)

The average heart rate has a significant influence on this component, indicating that PC1 is highly correlated with trends in average heart rate.

- *fcmax*: 0.479

Maximum heart rate also contributes significantly to this component.

- *fcmin*: 0.534

The minimum heart rate has a moderate contribution.

Interpretation of PC1: This component reflects an overall combined pattern of average, maximum, and minimum heart rate but is most strongly influenced by average heart rate (*fcavg*).

2) PRINCIPAL COMPONENT 2 (PC2)

- *fcavg*: -0.007 (Minimal contribution)

The average heart rate has very little influence on this component.

- *fcmax*: 0.749 (Predominant contribution)

The maximum heart rate significantly influences this component, indicating that PC2 is more related to the maximum values.

- *fcmin*: -0.663

The minimum heart rate contributes significantly but in the opposite direction (negative).

Interpretation of PC2: This component captures the relationship between the maximum and minimum values, emphasizing the extremes of the heart rates.

Therefore, PC1 is primarily related to the general trend of heart rates, particularly the average heart rate. PC2 reflects the contrast between the maximum and minimum rates, being more representative of the extreme variations. This approach aligns with previous studies demonstrating the utility of PCA in clustering physiological data for medical diagnosis [28].

To further assess the clustering performance, the following validation metrics were used:

Dunn Index: Evaluated the ratio between the smallest intra-cluster distance and the most significant inter-cluster distance, ensuring distinct cluster separation. The Davies-Bouldin Index (∼1.03) confirms that clusters are distinguishable but could be further refined.

Davies-Bouldin Index: Measures the compactness of clusters and their distinctiveness from one another. The Dunn Index (0.021) suggests that clusters may be too close together, indicating that alternative clustering techniques or additional feature engineering might improve results.

While the low value suggests relatively close clusters or some internal variability, it is balanced by the acceptable Davies-Bouldin Index (1.03) and Silhouette Score, which together indicate moderate to good clustering quality.

Finally, the software functionality was evaluated using a concordance study with the manually developed evaluation. For this purpose, the cardiac dynamics data collected by the smartwatch were analyzed in a sample of 24 subjects, divided into two groups: individuals with normal heart rates and those with pathological heart rates. Two types of analysis were performed on the collected information: the first was conducted manually, and the second utilized software developed for this purpose. In both cases, the following procedure was applied. Chaotic attractors were constructed using the maximum and minimum heart rate values per hour, as well as the total number of beats per hour. These attractors were analyzed to evaluate the occupied space, fractal dimension, and occupation probability in the generalized Box Counting space. Next, it was compared whether the results obtained by the software matched or, conversely, could not be satisfactorily replicated by the manual procedure. A diagnostic concordance study was subsequently conducted to compare the mathematical evaluation obtained with the conventional clinical review, considered the Gold Standard, to identify the strengths and limitations of the automated methodology. The study participants ranged in age from 23 to 92 years, with 41.67% being men and 58.33% being women. No significant differences were found between the manual measurements and those obtained through the software. When comparing the evaluation results obtained through the software with the Gold Standard, the values obtained for sensitivity and specificity were 0.42 and 1, respectively. Although the sensitivity of the adjusted system is low, its clinical utility is justified due to its high specificity. This means that the system is effective in ruling out false positives, as well as its accuracy, which is essential in clinical contexts where it is desired to avoid overdiagnosis or unnecessary alarms in healthy people. This showed strengths, such as maximum specificity, and limitations, including low sensitivity, in detecting pathological dynamics. According to the Landis and Koch scale, the Kappa coefficient reached a value of 0.34, indicating a low level of concordance with the Gold Standard.

V. DISCUSSION

This work represents one of the first approaches to integrating a custom (non-proprietary) smartwatch application that captures heart rate. It combines methodologies based on dynamical systems theory and fractal geometry. The results confirm the viability of this approach and highlight its clinical and technological potential.

The results evaluated the application's usability using the System Usability Scale (SUS), achieving a score higher than 80.3, which is similar to the results obtained by Han et al. [5]. According to Brooke [35], a SUS score above 68 is considered above average, indicating that users found the system to be intuitive, efficient, and easy to use. As noted by Ramin et al. [34], this value is consistent with the acceptability recommendations proposed in previous works, which underlines the ease of use and positive user experience. However, although the usability score is high, further improvements can enhance adoption in real-world settings and facilitate clinical integration. Studies have shown that even medical apps with high usability can face barriers in terms of long-term engagement, clinical compliance, and accessibility for diverse populations. Its adoption in clinical settings depends on seamless integration with electronic health records (EHRs) and telemedicine platforms [36].

One of the study's strengths is the application of innovative methodologies to analyze cardiac dynamics, including physical-mathematical techniques based on dynamical systems and fractal geometry, as proposed by Rodríguez et al. [10].

Additionally, software development for wearable devices, particularly for Android-based smartwatches, enables the capture of heart rate data from patients with a cardiac history and healthy individuals for 20 continuous hours. This configuration proved effective in obtaining consistent and differentiable data between both groups. The proposed smartwatch-based cardiac monitoring system integrates clustering analysis and fractal geometry to enhance heart rate analysis, distinguishing it from commercial heart rate monitoring solutions. The system does not yet match certified ECGs in terms of sensitivity, specifically in its ability to detect all arrhythmias. Still, it achieves high specificity, meaning that when it detects an abnormal condition, it is accurate.

The data collected were processed using the proposed methodology and statistically analyzed using the t-test. The results showed that the heart rates of the "Cardio" group were significantly higher than those of the "Healthy" group, which validates the diagnostic capacity of the method used. The data collected were processed using the proposed methodology and statistically analyzed using the T-Student test. The results showed that the heart rates of the "Cardio" group were significantly higher than those of the "Healthy" group, which validates the diagnostic capacity of the method used.

Furthermore, the clustering analysis applied to the data enabled the categorization of patients into three main groups based on their minimum, maximum, and average heart rates. These results agree with previous research, such as that of Kumar et al. [27], which highlighted the effectiveness of clustering algorithms in detecting patterns in physiological data. In this case, identifying clusters provided a basis for differentiating between normal and abnormal patterns in patients with cardiac conditions.

The smartwatch-based cardiac system, although with moderate sensitivity (0.42), stands out for its perfect specificity (1.00). While the sensitivity indicates that the system correctly identifies 42% of true positive cases (i.e., patients with the condition), the perfect specificity means it reliably excludes all false positives. This trade-off implies that although some affected patients may not be detected, those flagged as positive are almost certainly truly at risk. Therefore, the system is particularly valuable as a screening or triage tool, helping to prioritize further diagnostic testing, especially in non-clinical or resource-limited environments. The system demonstrates strong usability (SUS $>$ 80.3) and is grounded in a mathematically robust approach based on fractal geometry and clustering techniques. Unlike commercial ECG-based tools (e.g., Apple Watch, Pulsewatch), it analyzes heart rate variability through attractor dynamics, enabling nonlinear diagnosis and risk stratification. Its clustering model ($k = 3$) showed validated separation, thereby enhancing interpretability. While commercial devices rely on basic ECG or PPG, your system offers a data-driven, real-time alternative. Although not a replacement for Holters, it excels as a complementary screening tool, especially in resource-limited contexts. Supported by recent studies.

The study analyzed 272 Holter records and 25 samples from smartwatches. While the Holter dataset provides a solid foundation for developing the model, the smartwatch sample is relatively small, limiting the statistical power and robustness of the conclusions drawn from real-world usage. Larger, more diverse datasets are required to confirm generalizability.

Potential biases include Selection bias, as data were obtained from specific Peruvian healthcare centers, which may not reflect broader populations. Technology bias occurs when using only the Samsung Galaxy Watch 4, thereby limiting device-based variability. Labeling bias, given the reliance on clinical diagnoses as the gold standard, may have subjective variability.

Regarding real-world applicability, despite its limitations, the system shows promise for non-invasive, continuous cardiac monitoring, especially in resource-limited or remote settings. Its high specificity and good usability (SUS > 80.3) support practical adoption. However, for full clinical integration, broader testing across devices, populations, and clinical environments is necessary.

In summary, the study's findings highlight the potential of utilizing wearable technology and advanced data analytics in the diagnosis of cardiac conditions. Although significant progress has been made, it is essential to continue evaluating and validating these methodologies in clinical settings to consolidate their application.

VI. CONCLUSION

This study presents the development and validation of a novel smartwatch-based system for cardiac diagnosis and monitoring, which integrates fractal geometry, dynamical systems, and clustering analysis to enhance the interpretation of heart rate variability. The results demonstrate that the system is technically feasible, clinically promising, and highly acceptable to users.

From a diagnostic perspective, the integration of fractal dimension analysis and clustering techniques enabled the system to identify meaningful patterns in cardiac dynamics, categorizing patients into three distinct groups based on their average, minimum, and maximum heart rates. This method facilitates the early detection of abnormal cardiac behavior, providing an alternative to traditional ECG-based assessments, particularly in non-hospital settings.

Statistical evaluations using the t-test revealed significant differences between the cardiac conditions of the "Cardio" and "Healthy" groups, supporting the system's discriminatory power. Clustering validation using the silhouette score, the Dunn index, and the Davies-Bouldin index further confirmed the internal coherence and separability of the identified patient groups.

From a usability standpoint, the System Usability Scale (SUS) yielded a score of 80.3 or above, indicating excellent user acceptance. This suggests that the interface and interaction flow of the "Mi Cardio" application are suitable for both general and at-risk populations, supporting its implementation in real-world contexts.

Furthermore, concordance analysis between manual and automated evaluations demonstrated high specificity and moderate agreement with the clinical gold standard, validating the mathematical model and confirming its potential for assisting in cardiac diagnosis.

Future work will focus on extending the clinical validation of the system to more significant and diverse populations, enhancing algorithm sensitivity, and integrating AI-driven decision support to improve diagnostic precision. Additionally, the incorporation of secure data transmission protocols and interoperability with electronic health records (EHRs) will be prioritized to facilitate adoption in professional medical settings.

In summary, this research presents a robust, user-centered, and mathematically grounded tool for non-invasive cardiac monitoring, advancing the potential of wearable technology in the early detection and management of cardiovascular diseases.

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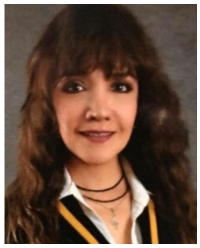

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