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Review

A Brief Review on Gender Identification with Electrocardiography Data

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Abstract: Cardiac diseases have increased over the years; thus, it is essential to predict their possible signs. Accurate prediction efficiently treats the patient's medical history before the attack occurs. Sensors available in commonly used devices may strive for the proper and early identification of various cardiac diseases. The primary purpose of this review is to analyze studies related to gender discretization based on data from different sensors including electrocardiography and echocardiography. The analyzed studies were published between 2010 and 2022 in various scientific databases, including PubMed Central, Springer, ACM, IEEE Xplore, MDPI, and Elsevier, based on the analysis of different cardiovascular diseases. It was possible to verify that most of the analyzed studies measured similar parameters as traditional methods including the QRS complex and other waves that characterize the various individuals.

Keywords: gender identification; electrocardiogram; cardiac diseases; sensors; systematic review

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1. Introduction

The prevalence of heart failure has increased over the past decades and is a significant social and economic burden on healthcare services [1,2]. Therefore, it is imperative to become aware of the presence of heart disorders in an individual [2,3]. Furthermore, in the medical field, it is essential to determine the occurrence of predicting heart diseases [4,5]. Accurate prediction efficiently treats a patient's medical history before the attack occurs [6,7].

A variety of signals acquired from different sensors can be used to identify cardiovascular diseases including the various mechanisms and principles of monitoring pulse signals as well as the flexible sensor monitoring of electrocardiogram (ECG), phonocardiogram (PCG), seismocardiogram (SCG), ballistocardiogram (BCG), and apexcardiogram (ACG) signals [8–10].

Gender is almost its most salient feature, and gender classification based on ECG signals is one of the most challenging problems in individual identification [11,12]. Unfortunately, compared with other research topics, academic research on gender classification based on ECG signals is scarce [13,14]. Nevertheless, successful gender classification will boost the performance of patient recognition in an extensive medical database [13,14].

Following a previous review related to the proposal of a methodology for the implementation of a system related to the 5P-medicine approach for cardiovascular patients [15], the motivation of this study was to include a new variable, leading to the development of the increased precision of the system. The 5P-medicine approach consists of the integration of five concepts: predictive, preventive, participatory, personalized, and precision medicine. Gender identification using acquired ECG data will promote the obtention of better results in the different concepts, providing a concrete prediction of an individual's health status, allowing preventive actions to be taken earlier according to the different ECG patterns. Finally, it will allow for the creation of a personalized and precise solution through the identification of the different characteristics of an individual, including gender and diseases, that will benefit the treatment and monitoring of cardiovascular patients.

This study briefly reviews the use of technological equipment and sensors focusing on gender classification based on ECG signals. The scope of this paper consists of the fact that such gender classification may empower treatments through their adaptation based on the characteristics of an individual when determining the presence of cardiovascular diseases or other related problems.

2. Materials and Methods

2.1. Research Questions

This systematic review was based on the following questions: (RQ1) Which methods can be used with ECG sensors for gender identification? (RQ2) Which features can be extracted from ECG sensors for gender identification? (RQ3) What are the benefits of using ECG sensors for gender identification?

2.2. Inclusion Criteria

The study of the methods and sensors for measuring the results of gender identification with electrocardiography was performed with the following inclusion criteria: (1) studies in which gender influenced the results; (2) studies that presented the purpose of the research; (3) studies that clearly defined the study of the study; (4) studies that presented the results; (5) studies presenting original research; (6) studies that were published between 2010 and 2022; (7) studies written in English.

2.3. Search Strategy

This systematic review consisted of studies that met the inclusion criteria in the following electronic databases: PubMed Central, Springer, ACM, IEEE Xplore, MDPI, and Elsevier. The following research terms were used to research this systematic review: "ECG disease classification", "ECG disease identification", and "ECG gender identification". An NLP framework was used to identify the relevant articles [16]. Every study was independently evaluated by the authors, determining their suitability with the agreement of all reviewers. The studies were analyzed to identify the various methods for using sensors to measure gender identification with electrocardiographic results. The research was performed on 10 April 2022.

2.4. Extraction of Study Characteristics

Several parameters were extracted from the various studies. The extracted data from the different studies are presented in Table 1 including year of publication, location, the population of the study, purpose, sensors used, and diseases present in the population analyzed. In general, the source code of the implemented methods and the dataset used were not available in the various studies and, consequently, they were not publicly shared.

Table 1. Study analysis.

Study	Year of Publication	Location	Population	Purpose	Sensors Used	Type of Method	Diseases
Król-Józaga [17]	2022	Poland	23 individuals	The study aimed to compare three two-dimensional representations.	Electrocardiogram	Statistical	Arrhythmia
Shehta et al. [18]	2021	Egypt	53 individuals	The authors aimed to detect subtle cardiac changes in Duchenne muscular dystrophy patients with electrocardiography and echocardiography sensors.	Electrocardiogram Echocardiogram	Statistical	Duchenne muscular dystrophy
Jiang et al. [19]	2020	China	3391 participants	The authors developed an artificial intelligence approach for the detection of left atrial enlargement.	Electrocardiogram	Machine Learning	Left atrial enlargement
Kapolas et al. [20]	2018	United States of America	137 patients	The study aimed to determine risk factors for the development of CA in patients undergoing HSCT.	Electrocardiogram	Statistical	Arrhythmia Coronary artery disease
Song et al. [21]	2018	China	23,417 patients	The study aimed to develop a risk model to predict in-hospital death among contemporary AMI patients as soon as possible after admission.	Electrocardiogram Echocardiogram	Machine Learning	Myocardial infarction
Keller et al. [22]	2016	Germany	175 patients	The authors investigated the ECG alterations of the right bundle branch block and SIQIII-type patterns for risk stratification in acute PE.	Electrocardiogram	Statistical	Bundle branch block
Valuckiene et al. [23]	2015	Lithuania	173 patients	The authors predicted ischemic mitral regurgitation in patients with acute ST-elevation myocardial infarction.	Angiogram Echocardiogram	Machine Learning	Coronary artery disease Myocardial infarction
Dewhurst et al. [24]	2014	United Kingdom	2232 participants	The authors aimed to establish electrocardiographic reference values for a population likely to differ genetically and environmentally from others where reference values are established.	Electrocardiogram	Statistical	N/D

Table 1. *Cont.*

Study	Year of Publication	Location	Population	Purpose	Sensors Used	Type of Method	Diseases
Miller et al. [25]	2014	United States of America	197 individuals	The goal was to determine if salivary biomarkers could facilitate a screening diagnosis of acute myocardial infarction.	Electrocardiogram	Statistical	Myocardial infarction
Couderc et al. [26]	2012	France	307 individuals	The study aimed at determining whether a harmful response to an increased heart rate leads to abnormal dynamic QT-RR profiles and may be responsible for the increased cardiac risk in these patients.	Electrocardiogram	Statistical	Congenital long-QT syndrome
Hussien et al. [27]	2011	Egypt	300 patients	The authors aimed to analyze the ST-segment elevation and the maximal QRS duration and correlated the values to predict left main and three-vessel disease.	Electrocardiogram	Statistical	Acute coronary syndrome Myocardial infarction Unstable angina
Vetter et al. [28]	2011	United States of America	400 participants	The study attempted to add an ECG to history and physical examination and to identify a methodology for a more extensive multicenter study.	Electrocardiogram Echocardiogram	Statistical	N/D
Kronander et al. [29]	2010	Sweden	1876 patients	The study compared the measurements of ST-segment changes during exercise and early postexercise recovery in terms of diagnostic discrimination capacity and optimal partition values.	Angiogram Myocardial Scintigraphy	Statistical	Coronary artery disease

3. Results

As presented in Figure 1, we identified 25,388 studies from the selected sources with automation tools. After the search, the automation tool excluded the duplicate records, amounting to 10,335 articles. Next, it filtered the scientific papers by their metadata, i.e., title, abstract, and keywords. It resulted in 14,907 studies being excluded from the analysis, because they did not directly relate to evaluating gender identification with electrocardiography signals. Next, the full text of the remaining 20 articles was assessed considering the inclusion criteria and, consequently, 9 scientific papers were excluded. Finally, the remaining 13 papers were examined and included in the qualitative and quantitative syntheses.

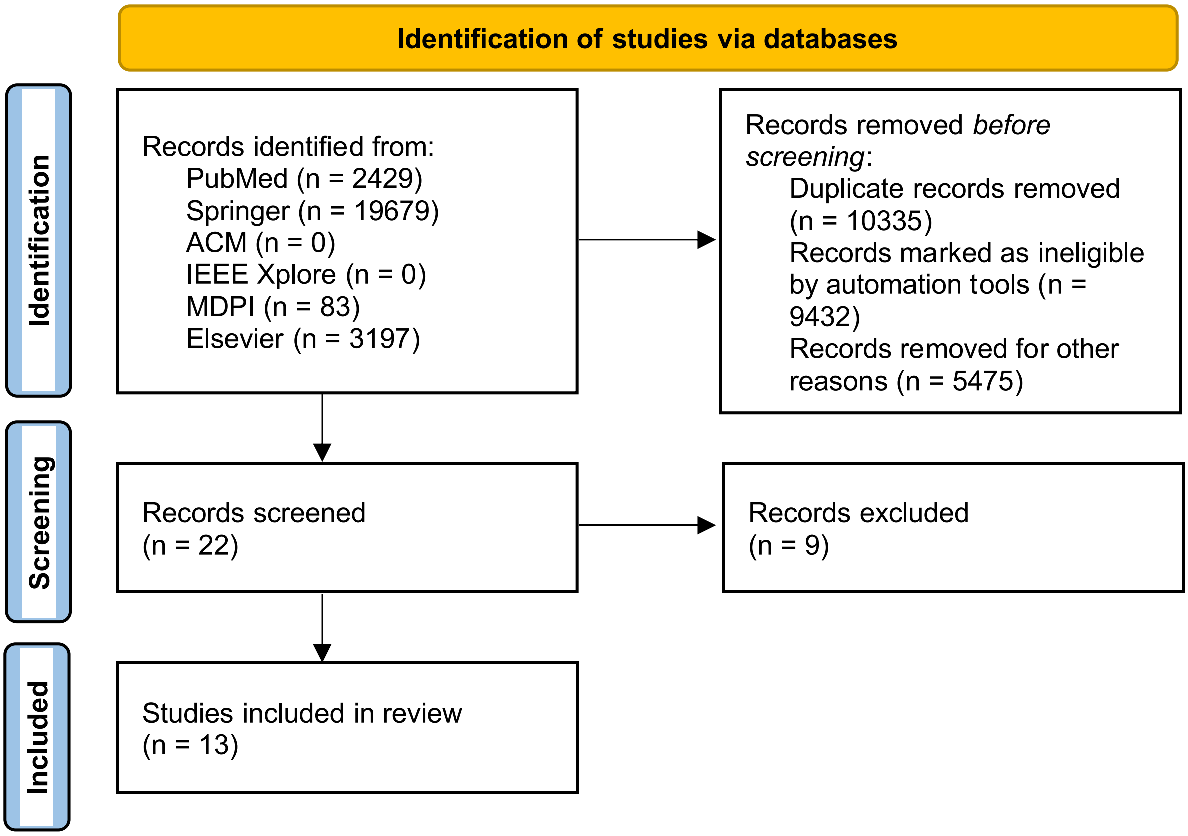

Figure 1. Flow diagram of the selection of the papers.

The studies were analyzed and selected, extracting the relevant information and metadata. The research performed in this study found research articles published between 2010 and 2022. As reported in Table 1, one study was published in 2022, one study was published in 2021, one study was published in 2020, two studies were published in 2018, one study was published in 2016, one study was published in 2015, two studies were published in 2014, one study was published in 2012, two studies were published in 2011, and one study was published in 2010. Identifying by type of sensors used, eleven studies used electrocardiography sensors, four used echocardiography sensors, two used angiography sensors, and one used myocardial scintigraphy sensors. According to the diseases among the studied population, three studies considered patients with coronary artery disease, four studies considered patients with myocardial infarction, two studies considered patients with arrhythmia, one study considered patients with Duchenne muscular dystrophy, one study considered patients with the acute coronary syndrome, one study considered patients with congenital long-QT syndrome, one study considered patients with left atrial enlargement, one study considered patients with Bundle branch block, and one study considered patients with unstable angina. Geographically, according to the origin of the studies, three were performed in the United States of America, two were performed in Egypt, two were performed in China, and the remaining were conducted in the United Kingdom, Lithuania, Germany, Poland, France, and Sweden. Finally, regarding the implemented methods in the different studies, three studies used machine learning methods, but the remaining only performed statistical analysis.

In [23], the authors used coronary angiography and echocardiography to predict ischemic mitral regurgitation (MR) in acute ST-elevation myocardial infarction patients (STEMI). The study considered patients with STEMI, whose examination was conducted 12 h after the onset of symptoms and were treated with primary percutaneous coronary intervention (PPCI) at the Lithuanian University of Health Sciences Hospital. Echocardiography was performed after PPCI. Based on the MR grade, patients were divided into groups without significant MR (NMR grade 0-I MR, $n = 102$) and ischemic MR (IMR, grade ≥ 2 MR, $n = 71$). Well-developed adverse symptoms were identified as a class ≥ 2 according to the Rentrop classification. The Student's t-test was used to compare continuous variables with independent samples. Independent predictors of ischemia MR were found based on multivariate logistic regression analysis.

Kapolas et al. [20] used The Statistical Analysis Software to determine the risk factors for the development of cardiac arrhythmia (CA) in patients undergoing hematopoietic stem cell transplantation (HSCT). The experiments were performed with 138 consecutive patients undergoing HSCT at their institution between 1 January 2015 and 31 December 2017. Thirty-one patients (23%) had CA while undergoing HSCT. Atrial fibrillation was the most prevalent form ($n = 13$; 42%). Non-Hodgkin's lymphoma diagnoses were associated with a higher frequency of CA (17/31; 54.8%) compared to a lower frequency of CA (7/106; 6.6%) and a QTc > 500 milliseconds at any point during transplantation (8/31; 25.8%) compared to a QTc < 500 (6/106; 5.6%) ($p = 0.0011$).

The authors of [22] used the ECG parameters of the right bundle branch block (RBBB) and S_IQ_{III}-type patterns to investigate the ECG parameter changes for risk stratification in acute pulmonary embolism (PE). The experiments were performed on patients with a confirmed diagnosis of acute PE treated at the Internal Medicine Department between May 2006 and June 2011. The analyses were performed by 175 patients treated at the Internal Medicine Department and were included in this retrospective analysis. The research sample included 138 PE patients (78.9%) without both symptoms and 37 PE patients (21.1%) with RBBB and S_IQ_{III}-type patterns. Heart rate (97.4 ± 17.2 vs. 93.2 ± 26.8/min, $p = 0.021$), cardiac troponin I levels (0.19 ± 0.38 vs. 0.11 ± 0.24, $p = 0.003$), and the ratio of patients with RVD (83.9% vs. 52.7%, $p = 0.005$) were all substantially greater in PE patients with RBBB and S_IQ_{III}-type pattern alterations. Significant correlations between RBBB and RVD were found with multivariate logistic regression models adjusted for age and gender (OR 3.942; 95 percent CI 1.054–14.747; $p = 0.042$) and between S_IQ_{III}-type patterns and RVD (OR 5.667; 95 percent CI 1.144–28.071; $p = 0.034$). While the correlation between S_IQ_{III}-type patterns and cardiac damage was significant (OR 3.956; 95 percent CI 1.309–11.947; $p = 0.015$), the correlation between RBBB and cardiac injury (cTnI N 0.4 ng/mL) revealed a borderline significance (OR 2.531; 95 percent CI 0.973–6.583; $p = 0.06$).

In [17], the author compared two-dimensional representations of ECG in three different approaches. The emphasis was placed on maintaining stable conditions to determine the features and validate the proposed methods. The participants had atrial fibrillation, and the results obtained for the spectrogram and scalogram were similar and confirmed the effectiveness of the processes in detecting atrial fibrillation. Attractor reconstruction was inferior to the other two but still effective.

Miller et al. [25] analyzed data with concentration cut-points, ECG findings, logistic regression (LR), and classification and regression tree (CART) analysis. Within 48 h of the commencement of their chest symptoms, 92 patients with acute myocardial infarction underwent the examinations, along with 105 asymptomatic healthy controls. In addition, they repeated the CART analysis on 58 cases and 58 controls, ones that were matched for age and gender, allowing for a sensitivity analysis to be carried out. As evaluated by LR and CART, this investigation showed that serum biomarkers had higher acute myocardial infarction sensitivity and specificity than saliva.

The authors of [21] used ECG and echocardiogram (ECO) in patients with acute myocardial infarction from the China Acute Myocardial Infarction (AMI) registry from January 2013 to September 2014 to develop a risk model to predict in-hospital death among contemporary AMI patients as soon as possible after admission; 541 (9.3%) individuals with NSTEMI who had an early invasive approach did so. Among the patients with STEMI, 1739 (9.9%) received thrombolytic treatment, whereas 7587 (43.2%) patients had primary PCI.

In [24], the authors used a 12-lead electrocardiography in 2232 healthy community-based participants without known cardiac disease aged 70+ in rural Tanzania. Digital electrocardiograms were analyzed, and after univariate analysis of the covariance using a multiple linear regression model, adjusting for age; systolic blood pressure (SBP); body mass index (BMI); RR interval; gender-specific reference values for the P duration (PD), P amplitude (PAMP), P area (PAREA), P terminal negative force (V1) (PTNF), PR interval, QRS duration (QRSD), and QT/QTc. In this genetically and ecologically varied SSA community, reference values for comprehensive electrocardiographic parameters were developed, allowing for “outliers” who may have heart illness yet to be identified.

Kronander et al. [29] used angiography, myocardial scintigraphy, and clinical grounds in 1876 patients undergoing a routine bicycle exercise test. Angiographically, coronary artery disease (CAD) was confirmed in 668 individuals. At the same time, it was ruled out in 119 patients by angiography, 250 patients through myocardial scintigraphy, and 1208 patients through clinical grounds (n = 839). During the first three minutes of recovery, postexercise ST/HR hysteresis was normalized for the heart rate (HR) ST/HR loop area. By dividing the total change in ST amplitude during exercise by the change in HR brought on by exercise, the ST/HR index was calculated. During exercise, the ST/HR slope was determined using a linear regression analysis of the ST/HR data pairs. A three-minute period before and after the activity was used to detect ST-segment depression. The findings showed that the most precise and gender-neutral method of identifying patients with CAD was a postexercise ST/HR hysteresis study.

The authors of [18] intended to conduct a study to detect subtle cardiac alterations in patients with Duchenne muscular dystrophy using electrocardiography and echocardiography. For this purpose, a study was carried out on patients genetically diagnosed with Duchenne muscular dystrophy. The study had a set of 53 patients, where 28 were male and 25 females. The participants had clinical evaluations and were submitted to 12 amusements of electrocardiograms and global echocardiograms with longitudinal strain and a control group divided by gender. Patients with Duchenne muscular dystrophy had smaller left ventricular and left atrial internal diameters, higher heart rates, and lower ejection fraction, and there existed worse left ventricular global longitudinal strain compared to the control group’s results. These results demonstrate that mutations in exons 45–47 and 51–54 were associated with an ejection fraction of less than 60%. In summary, the authors considered that the assessment of global longitudinal strain was able to detect left ventricular systolic dysfunction in patients and carriers before the decline in ejection fraction.

In [27], the authors carried out a study with the objective of the early identification of patients with LM/3VD disease, which is a possible solution in the prognosis and selection of the ideal treatment strategy in patients with NSTE-ACS. The study was carried out with 150 patients who had acute coronary syndromes without ST-segment elevation, 70 patients who had unstable angina from January 2009 to January 2010, and 80 patients who had non-ST-segment elevation myocardial infarction. All patients had a complete medical history as well as clinical examinations. In addition, the authors performed ECG analysis to assess the degree of ST-segment elevation in aVR, ST-segment depression in other leads, the maximum QRS interval, and angiographic data during hospitalization. Based on the tests carried out in the study, they concluded that ST-segment elevation in variation with a QRS duration of 90 ms was a good cardiographic predictor of the left trunk and three-vessel disease in patients with non-ST segment chronic sharp syndrome.

Vetter et al. [28] aimed to carry out a pilot study to examine healthy, young people in the USA to assess the conditions that lead to sudden cardiac arrest in healthy, young people. Accordingly, a study was carried out with 400 healthy, young people, between 5 and 19 years old, using a questionnaire on medical and family history, weight, height, blood pressure, heart rate, cardiac examination, ECG, and ECO, with the primary objective of evaluating the feasibility of adding an ECG exam to the physical exams of young people and identifying a methodology to be used in a multicenter study. Based on the results of the evaluations, 23 young people were identified with cardiac abnormalities and 20 with hypertension, and 10 with severe cardiac conditions. In summary, the authors concluded that the performance of ECG and ECHOs in young people is viable for detecting illnesses linked to sudden cardiac arrest.

The authors of [26] aimed to demonstrate the hypothesis that a harmful response to increased heart rate leads to abnormal dynamic QT-RR profiles and may be responsible for the increased cardiac risk in these patients. For this purpose, a study was carried out to measure the slope of the QT-RR in 24 h ECGs with a group of 18 patients with LQT-1 mutations associated with impaired adrenergic stimulation and compared with 48 patients with LQT-1, where there was one patient with other mutations and a control group of 195 patients. Based on the study performed, the authors concluded that patients with C-loop LQT-1 have impaired adrenergic regulation of ventricular repolarization. This response to cardiac augmentation may allow for the identification of high-risk patients with prolonged hereditary QT intervals.

In [19], a study was carried out to develop an artificial intelligence approach for the detection of left atrial enlargement (LAE) based on a 12-lead ECG. To carry out the study, the author had a population of older adults over 65 with a 10 s 12-lead ECG, totaling 3391 patients. Based on echocardiograms, the author trained a convolutional neural network (CNN) to detect LAE from normal ECGs. As a result, the authors concluded that it was possible to identify patients with a high probability of LEA using artificial intelligence and ECG. However, the model needs further refinement and external validation.

4. Discussion and Conclusions

This study verified that only a few studies available in the literature using electrocardiography sensors allow for the discretization of gender. However, these studies allowed us to identify which sensors can be used for gender identification with reliable accuracy. There are no previous literature reviews regarding gender identification, but gender can handle the creation of personalized solutions for cardiovascular patients by gender.

This article performed a systematic review of the sensors and automated approaches to identifying the gender of the patients based on different parameters calculated by the sensors' signals and the diseases present in the population. Only thirteen studies were considered relevant per the inclusion criteria, which means this area may be an attractive field for future research. In line with this, this topic may be essential for facilitating the identification of diseases and their evolution.

From the thirteen studies identified in this review, the main findings are as follows:

- *(RQ1) Which methods can be used with ECG sensors for gender identification?* The main methods used were multiple linear regression, the logistic regression model, classification and regression tree analysis, the linear regression model, spectrograms, scalograms, Rentrop classification, and attractor reconstruction;
- *(RQ2) Which features can be extracted from the ECG sensors for gender identification?* The features extracted from the ECG sensors that can be used for gender identification were mainly the RR interval, the degree of ST-segment elevation, the ST-segment depression, the maximum QRS interval, the P-duration, the P-amplitude, the P-area, the P-terminal negative force, the PR-interval, the QT/QTc, and the slope of the QT-RR;

- *(RQ3) What are the benefits of using ECG sensors for gender identification?* The benefits of using ECG sensors are the possibility of analyzing the differences in the ECG waves of different genders and using this to study and treat heart diseases. The different treatments can be adapted by the different characteristics related to gender, and different treatments can be standardized by gender to promote the automation of the prescription of different medicines.

There was a lack of studies related to gender identification. However, the sensors may increase the reliability of the measurements of the electrocardiogram's performance, and this empowers various diagnostics in health. This review allows for the verification that there are different characteristics of ECG signals that can allow for gender identification, opening the possibility for the creation of personalized medical solutions.

In future work, we intend to use a labeled database [30] to implement different artificial intelligence methods for gender identification. This study will only be a preliminary study that needs to be validated with other labeled databases to create a reliable method for using ECG data for gender identification. Nevertheless, it can empower different types of patients and improve medical treatments.

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