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A survey on various machine learning approaches for human electrocardiograms identification

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Abstract

Human identification is a critical function that can aid in data security protection. Developing deep learning models for human identification from electrocardiogram (ECG) data is one of the most promising strategies. It has a number of specific advantages, including the identification of liveness, insensitivity, ease of collecting, and greater security. On the other hand, present classifier-based methods can only identify closed sets, whilst existing matching-based methods are computationally intensive. Additionally, virtually all algorithms analyze only one-shot identification, which is subject to noise. In light of the fact that the electrocardiogram (ECG) is the most often used diagnostic tool for monitoring electrical activity in the heart, it is critical to use it to find early detection and diagnosis signals. The rapid growth and adoption of electronic health records, which include a systematized collection of various types of digitalized medical data, along with the development of new methods for quickly evaluating this massive amount of data, has resurrected interest in the fields of machine learning and deep learning in recent decades. The purpose of this article is to provide an overview of the EKG's significance in terms of learning approaches, as well as a comparison of the most well-known research and technical phrases relating to the electrocardiogram.

Keywords: Human identification, Electrocardiograms, Heart, Machine Learning, Deep Learning, Recognition
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1. Introduction

Because of the rapid advancement of Ai Technologies, information security has emerged as a major source of concern for everyone in the world. Because it collects unique data from individuals and uses that data as a "key" to personal information, human identification is crucial in many situations. Among the most well-known methods of human identification, fingerprints, facial scans, and iris scans are all used [36]. ECG is an abbreviation for electrocardiogram, which is a type of physiological signal that records the electrical activity of the heart muscle over time and is used to diagnose cardiac disease. ECG patterns (such as P waves, QRS complex, and T waves) may appear to be similar among individuals, but their intricacy can differ due to differences in age and gender as well as differences in height, weight, and even lifestyle. Athletes, for example, have a larger QRS complex than the general population due to their stronger left ventricle [25].

Due to the fact that persons have few distinguishing characteristics, their ECG morphology also varies, allowing us to use ECG for human identification [43]. Electrocardiograms (ECGs) have proved critical in the investigation of cardiovascular problems. It has a broad range of applications in cardiovascular disease clinical diagnosis and prognosis, as well as health assessment, biological recognition, and fatigue research, among others [64]. Each patient's electrocardiogram (ECG) is monitored in standard clinics to show the activity of the human heart. To assess a patient's heart status, a physician usually records his or her ECG, which is commonly done with a device called a Holter monitor [29].

Biomedical signals provide critical information about human health because they demonstrate how the body's systems operate. The most frequently used piece of information by clinicians to determine the cardiac system's health is information about the heart's electrical activity [16]. Arrhythmias and other abnormalities in one or more phases of the cardiac cycle pattern, such as electrical conduction or tissue malformation, can induce arrhythmias and other issues. When the heart beats excessively early, excessively late, slowly, rapidly, or at irregular intervals, this is referred to as arrhythmia [30]. ECG technology is a novel biometric identification technique that is currently being investigated in the field of identification technology [13]. An ECG (Electrocardiogram) signal is a form of biological data that possesses unpredictability, uniqueness, and a high degree of difficulty of replication and fabrication, and can be used to validate biological identity. The ECG signal's characteristics are examined, as well as its utility as a form of identification [67].

When it comes to electrocardiogram (ECG) analysis, computer tools can assist physicians in completing time-consuming activities (such as Holter ECG monitoring in Intensive Care Units) or recognizing potentially harmful occurrences more quickly (e.g., ventricular fibrillation). ECG is being explored in the realm of biometrics (personal identity) in addition to its clinical uses (arrhythmia diagnosis and heart rate variability investigations), which is a rapidly expanding field of research. There are several different ways to biometrics used in therapeutic applications [52]. The electrocardiogram (ECG) is a vital sign that has been extensively investigated and is frequently utilized in clinical practice [25]. It is possible to visualize the electrical activity of the heart as a graph plotted against time using an electrogram of the heart [41].

2. Background Of Electrocardiogram ECG

More than a century ago, researchers discovered that the electrical currents of the heart could be measured. However, Willem Einthoven, a Dutch scientist who was awarded the Nobel Prize in physiology or medicine in 1924 for his work, was the first to develop the ECG as we know it today at the turn of the twentieth century [19]. Consider A cardiac electrocardiogram (ECG) is one of the most important complementary medical tests that can be performed with a cardiograph to look for and evaluate heart problems through waveform recording, which is the recording of changes in electrical potential between two points that occur during the electrical activity of the heart. An ECG is one of the most important complementary medical tests that can be performed with a cardiograph to look for and evaluate heart problems [45]. The physiologic basis for the ECG and how to monitor the ECG signal next Figure 1 shows the electrocardiogram (ECG) in a healthy human:

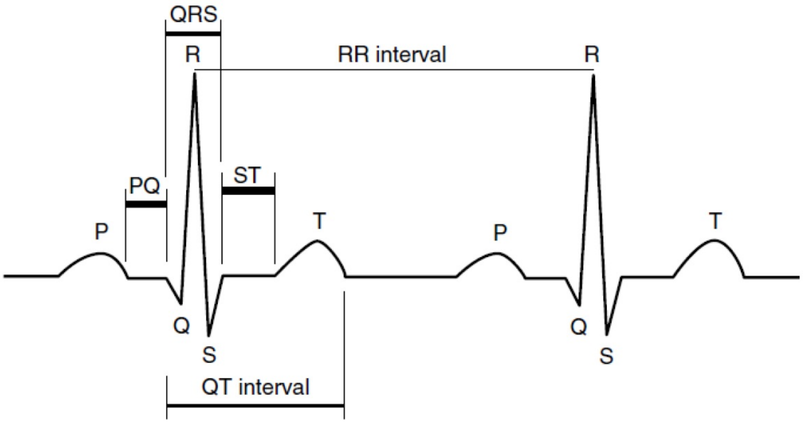


Figure 1: Electrocardiogram ECG in Human Healthy

And we can describe the above figure as the following table 1 to show what meaning the symbol abbreviation:

Table 1: Symbol Abbreviation in ECG [11].

symbol	Meaning	Description
Q	Wave	An initially negative deflection of the QRS complex
R	Wave	The first upward deflection following the P wave, as well as a portion of the QRS complex
S	Wave	This is the QRS complex's first downward deflection following the R wave.
P	Wave	Atrial depolarization is represented by the p wave, which is the first positive deflection on the ECG.
RR	The amount of time that has passed between two consecutive R-waves of the QRS signal.	It is determined by the sinus node's inherent features as well as autonomic factors. Blood pressure and vascular resistance (an indication of arterial constriction or dilation) have a convoluted relationship (the blood volume being pumped by the heart in 1 minute).
QRS	The complex represents ventricular depolarization.	It represents the electrical impulse as it goes through the ventricles to portray ventricular depolarization. Like the P wave, the QRS complex begins shortly before ventricular contraction.
PQ	Isoelectric (AV delay)	The speed with which the action potential is transferred through the AV node (also known as the PR interval because a Q wave is not always present).
T	wave	Represents ventricular repolarization.
ST	Isoelectricity refers to the action potential of a ventricular myocyte's ventricular potential plateau.	There is a period of time between ventricular depolarization and ventricular repolarization, which is sometimes referred to as the end of the QRS complex and the commencement of the T wave.
QT	The amount of time that has passed since the beginning of the QRS complex	The QT interval is defined as the time interval between the start of the Q wave and the end of the T wave, or the time interval between the start of the Q wave and the end of the T wave in the case of a heart rhythm disorder.
U	wave	It occurs following the T wave of ventricular repolarization and, because to its tiny size, may not always be visible. Purkinje fiber repolarization is considered to be represented by "U" waves.

In the past, the term "ECG" has referred to a 12-lead electrocardiogram (ECG) taken while laying down, as stated further below. A Holter monitor, for example, can be used to record the electrical activity of the heart over time [35], and some smartwatch models can also record an ECG (beginning with the Apple Watch, ECG signals can be recorded in other scenarios with other devices) [39]. The stretcher of 12-lead placement in ECG is shown in Figure 2:

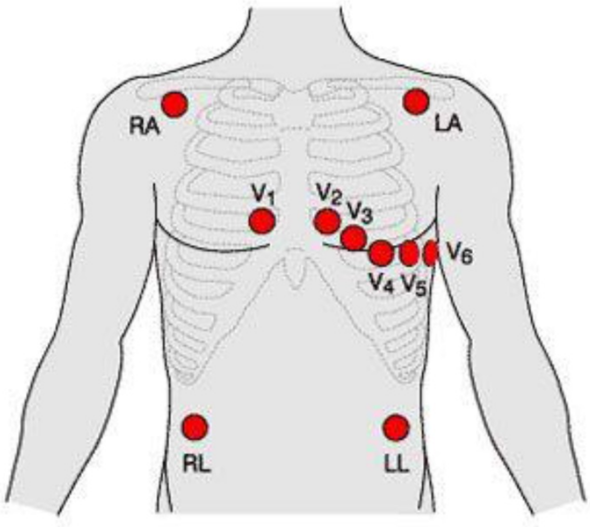


Figure 2: 12-Lead Placement in ECG [49].

3. Problem Background

Human identification is a critical responsibility that may contribute to the preservation of data security. In Table 2, we describe the problem that previous researchers have found to be effective and based on their research:

Table 2: Summrazed of Problem Background

NO	References	Description
1	[25]	Recognition and human identity detection systems are among the latest systems that can be developed rapidly. All the famous identification systems such as eye prints, iris, fingerprints, voice, and face suffer from some kind of inaccuracy due to the external formation. The electrocardiogram, on the other hand, is one of the fingerprints that cannot be duplicated in more than one person, and it is unilateral and unaffected by external formal factors such as cosmetic surgeries, wounds, formal manipulation, and so on.
2	[67]	Currently, there is no universal definition of the ECG boundary position. The ECG signal obtained by the ECG equipment is difficult to precisely characterize, and each measurement has corresponding variations that have a direct impact on the system's recognition ability.
3	[52]	Because in the recognition process, one-to-many identification is frequently encountered, the classifier's decision to output recognition results is critical. The performance of the classifier will be susceptible to a considerable amount of computing control when it is used in a large database with a large amount of data.
4	[16]	During the acquisition of an ECG signal, there are numerous interferences, disturbances, and artifacts, making it difficult to extract feature parameters and reducing waveform accuracy.

The researchers investigated whether an electrocardiogram (ECG) could be used as a biometric for secure and trustworthy human identification [55].

4. DRI (Detection, Recognition and Identification)

It means (Detection, Recognition, and Identification) and these are the types of techniques through which human identities are identified or examined, and the next table 3 shows the difference between the three terms:

Table 3: System Type Techniques [44]

NO	Name	Description
1	Detection	The ability to distinguish between a 'thing' and nothing.
2	Recognition	The ability to distinguish between different types of things (person, animal, car, etc.)
3	Identification	The ability to distinguish one person from other people.

4.1. ECG Recognition System

The electrocardiogram (ECG) is the most effective tool for establishing a person's identity since it is a recording of electrical activity in the heart that shows the rhythmic patterns of heartbeats. It is possible to gather a biometric sample from a real and living human because of the ECG's inherent vitality detection capacity. By including ECG as a biometric, the system's dependability is strengthened, and it becomes more resistant to fraudulent activity [55]. Signal processing, pattern identification, and machine learning approaches were used by the researchers to demonstrate the ECG's individuality among people. ECG morphology can be distinguished by its individual variations, as demonstrated in Figure 1. (3). It is the shift in ionic potential, electrolyte concentrations in the plasma, and rhythmic changes that all contribute to the ECG's characteristic look and appearance [32].

A specific pattern in an individual's pulse rhythm may also be manifested as a result of physiological differences in the thorax, such as chest geometry, heart position, size, and physical status [9]. It is the cumulative effect of this individuality that is reflected by alterations in the shape of the heartbeat, amplitude variances, and time intervals of the major components in the heartbeats of individuals. In addition, the information provided in the ECG can be utilized to diagnose a range of illnesses, including cardiac arrhythmias, according to the American Heart Association [1]. During the COVID-19 outbreak, for example, a patient's shortness of breath might be assessed using his or her ECG before further pathological investigations. It is possible for respiratory and circulatory difficulties to be caused by a pulmonary disorder because all internal body systems are interrelated and the lungs are the heart of the respiratory system. Off-the-person devices that gather ECG signals without requiring users to be present make it more convenient and comfortable for users to obtain ECG signals through skin or finger contact [14].

The development of sensing technologies has heightened interest in the study of electrocardiograms (ECGs). It investigates the prospect of using electrocardiograms (ECGs) as a non-obtrusive biometric, akin to fingerprints. An ECG, for example, can now be obtained simply contacting the electrodes with fingers, similar to how fingerprints are obtained. A novel technique known as "Jetson," which gathers ECG data from a distance, may be able to make ECG biometrics less obtrusive, comparable to the way that face and gait biometrics are used now. Therefore, there is a very good chance that the ECG will be acknowledged as a biometric by the general public [42]. However, the effectiveness of non-intrusive ECG data collection methods will be decided by the quality of the signal collected, as well as the capacity to collect specific characteristics of individual heartbeats. As a result, the ECG signal's preprocessing and characterisation are straightforward. In accordance with research, ECG readings collected through skin or finger contact are frequently contaminated with noise and other anomalies [18].

The availability of smarter equipment that can not only capture excellent data in an unobtrusive manner but also have the capability of gathering a unique feature of a person's pulse for their reliability will decide the success of ECG biometrics. Additionally, the ECG signal pretreatment and data representation approaches must be robust enough to allow for a biometric experiment with superior recognition. Examine and evaluate both of these concerns to see if they are successful in this study [61].

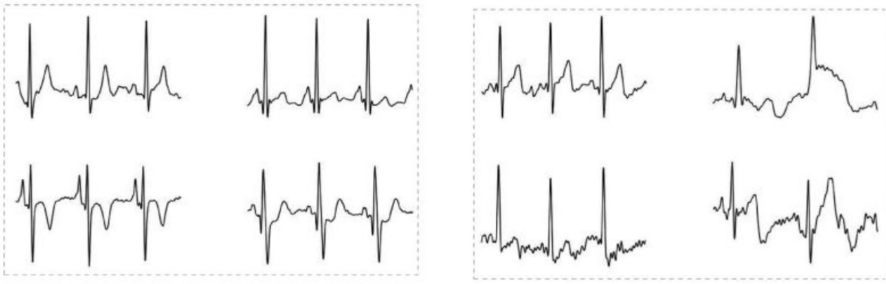


Figure 3: Representative ECG images [53].

In general, the algorithms used by most researchers may be split into two types: machine learning and deep learning. Machine learning is the method used in the majority of research projects.

4.2. ECG Recognition Process

The biological system is nothing more than a pattern recognition system for biometric data processing; it extracts feature points from the obtained data and compares them to a database template to determine whether or not the data is valid [23]. Depending on the application context, the biometric system can operate in either verification or identification mode. The verification pattern is a pair of one-to-one matchings that compare a biometric feature registered with a template database registration, and the identification pattern is a pair of one-to-one matchings that compare a biometric feature registered with a template database registration. If these two characteristics remain constant, the visitor is valid; if they do not, the visitor is illegal and should be refused entry [69]. According to what can be seen, the database identification code for the verification mode must be a unique identification number, whereas the biometric information must be identical to that used in the password verification method. All of the information gathered from visitors must be kept in the template database [71].

In the verification mode, the system is validated by comparing the biometric data obtained with the biometric template stored in the system database in order to authenticate a person's identity. Each one-to-many comparison between the real-time feature and all biometric templates is done many times, resulting in a unique identifying pattern. The identification mode is mostly employed in the sphere of public safety to find out the feature information of the matching biometric features from the template [46]. Figure 4 General process of identity recognition based on ECG signal

5. Methods in ECG Technical

There are two types of methods used in identification systems through electrocardiograms, which are deep learning and machine learning. The following is a table 4 showing the most important differences between these two types:

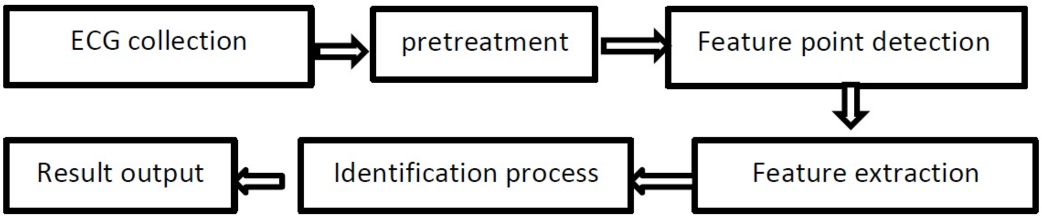
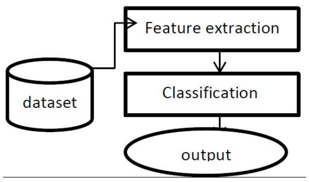
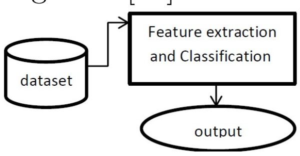


Figure 4: General process of identity recognition based on ECG signal: [46]

Table 4: Machine Learning vs. Deep learning [66, 63]

Machine learning	**Deep learning**
Definition: Machine learning (ML) is a sort of artificial intelligence (AI) that allows software applications to improve their prediction accuracy without having to be expressly developed to do so in the field of AI. To predict future output values, machine learning algorithms use historical data as input. Machine learning is a technique that is widely employed in recommendation engines. Fraud detection, spam filtering, malware threat detection, business process automation (BPA), and predictive maintenance are just a few of the applications that are commonly used.	Definition: An artificial neural network may be used to do complex computations on huge quantities of data when used in deep learning. Human brain shape and function are the basis for this new sort of machine learning, which is really interesting. Deep learning algorithms, which are algorithms that learn by seeing and repeating instances, are used to teach machines. One of the most common uses of deep learning is in the fields of health care and e-commerce as well as in entertainment and advertising.
Example: (Linear Discriminant Analysis -LDA), (Support Vector Machines SVM), k-nearest neighbors –KNN)	Example: (Convolutional Neural Network-CNN), Long Short Term Memory Networks (LSTMs), Restricted Boltzmann Machines(RBMs).
Work: To teach computers to think like people, machine learning, a type of artificial intelligence (AI), is used, which builds on and improves on prior experiences. Without any human assistance, it analyzes data and discovers patterns. When a data-defined pattern or set of rules is used to execute an action, machine learning can automate practically any operation that can be accomplished. Businesses can use this technology to automate tasks that were previously performed by humans, such as answering customer service calls, bookkeeping, and reviewing resumes, among other things.	Work: Deep learning algorithms employ self-learning representations, but they also use artificial neural networks (ANNs) that mimic the way the brain processes information. Machine learning algorithms employ unknown input components to extract features, arrange objects, and find significant data patterns during the training phase of the method. This occurs on numerous layers, with algorithms used to construct the models, similar to how robots are trained for self-learning. Deep learning models employ a variety of algorithms. While no network is perfect, some algorithms are more suited to certain tasks than others. To choose the finest, it is vital to have a firm grasp on all of the key algorithms.
Figure 5 [33]:  Figure 5	Figure 6 [33]:  Figure 6

5.1. Machine Learning Models

The popular techniques for data mining are classification, cluster analysis, association rules, sequential pattern discovery, regression, and prediction. Algorithms for machine learning are classified into three major groups [62]:

- **Supervised Learning [7]:** Models like these require individual training so that during train-

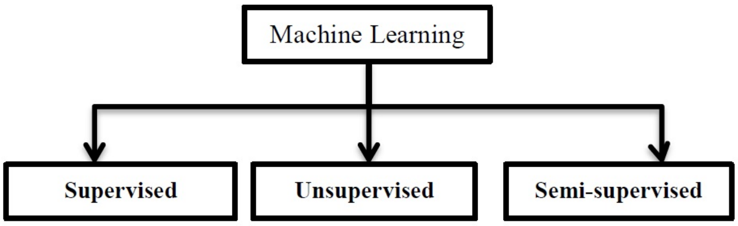


Figure 7: Machine Learning Models type [62]

ing of a particular machine learning model, the data analyst can provide input data and expect results. To make predictions, the data analyst will define the variables or features that the model analyzes and uses. New data can be predicted after training based on what the model is taught during the training process. The model is shown during the training process, and new data can be anticipated after training. The result is restricted to specific values, including filtering emails into "spam" classes and "not spam" classes in classification algorithms. Regression algorithm results are therefore continuous and may, in a range such as a temperature or the price of a commodity, have some value.

- **Unsupervised Learning [58]:** Models of this kind are used without labeled responses to create inferences from input data. This type of algorithm is used to identify patterns and other data structures, such as data point clustering, which is used to identify data groupings or secret patterns.

- **Semi-supervised learning [59]:** This method of machine learning is a combination of the two ways described above. It is possible for data scientists to provide an algorithm with an enormous quantity of "training data," yet the algorithm has complete freedom to explore and learn from its surroundings.

Cluster analysis is the most commonly used non-supervised learning approach, and it is used to analyze exploratory data in order to discover hidden patterns or categorize them into data sets. The clusters are built on the basis of a similarity measure defined in terms of metrics such as Euclidean distance or probability. At present, the efficiency of machine learning and deep learning has been shown in classifying photos, audio processing, and other information processing applications [33].

5.2. ECG in Machine Learning

The classification of electrocardiogram (ECG) signals is crucial in the diagnosis of cardiovascular diseases. Precision in ECG categorisation is a challenging topic to address. This study contains a survey of ECG classification into different types of arrhythmias. In order to diagnose heart abnormalities and determine a patient's treatment options, it is necessary to make an early and correct diagnosis of the various types of arrhythmia. ECG classification can be accomplished through the use of a variety of classifiers, with artificial neural networks becoming the most popular and widely used classifier for ECG categorization during the last several years. Techniques for preprocessing, ECG databases, feature extraction techniques, classifiers, and performance measures are all thoroughly discussed in this book, which is divided into four sections [28]. When the heart beats, the electrocardiogram (ECG) records the electrical activity. The A P, QRS, and T waves are all recorded. The extraction and segmentation of ECG features are critical in the detection of the vast majority of heart disorders [47]. The major goal of the following table is to study and present several machine learning approaches, as well as compare and contrast different methods and outcomes utilized to analyze the ECG.

Table 5: Approaches of ECG in ML

Reference	Approached	Description	Limitation
[48]	Fuzzy Based Techniques	There is a method that is widely utilized for performing effective ECG analysis that is simple and straightforward. Smooth variables with membership functions are employed in these ways for diagnosing disorders through the use of electrocardiograms. Another conventional definition is as follows: The term "fuzzy" refers to something that is a little foggy in its meaning. When a scenario is unclear, the computer may be unable to determine whether a true or false response should be given by it. In Boolean logic, the number 1 represents "True," while the value 0 denotes "False." Unlike a traditional logic algorithm, a fuzzy logic algorithm takes into account all of a problem's uncertainties, including the potential of receiving an answer other than True or False.	Because these systems rely on erroneous data and inputs, their accuracy is jeopardized. The use of Fuzzy Logic to a problem does not have a one-size-fits-all solution. There are multiple solutions to the same problem as a result of this, which makes the situation complicated. Because of the unreliability of their results, they are not generally well-regarded. Because fuzzy logic control systems are completely reliant on human knowledge and expertise, they suffer from a number of serious drawbacks. The rules of a Fuzzy Logic control system must be changed on a regular basis. These platforms do not consider machine learning and neural networks as valid methods of learning. Extensive testing is required for the purposes of system validation and verification.
[27]	Rough Set Theory and Hidden Markov Model Rough Set Theory and Hidden Markov Model	Rough Set Theory (RST) was developed in the early 1980s as an approach for removing uncertainties and ambiguity from data (the problems that RST solves are related to the reduction of redundant data, the discovery of data dependencies, data classification, and data pattern assessment). Furthermore, utilizing RST in ECG analysis has the benefit of assisting in the formulation of simple rules that lead to correct results. The extraction of important data from large databases.	When massive amounts of data must be encrypted simultaneously by the same computer, the RSA approach can be quite slow. It demands the involvement of a third party to validate the public key's security. Data transmitted via the RSA algorithm is susceptible to manipulation by intermediaries who control the public key system. To summarize, the encryption of sensitive data requires both symmetric and asymmetric encryption approaches.
[5]	Approaches based on Neural Networks	Neural networks are used for classification after preprocessing, detection, and feature extraction from the ECG signal	The network's performance is directly affected by the network's hardware dependency, unexplained network operation, network structure assurance, and the display mechanism to be determined.
[44]	Approaches using SVM	Performance of the network will be affected by factors such as the network's hardware dependency, the network's unexplained functioning, and the network's structure assurance.	The VM approach is ineffective when dealing with large datasets. SVM does not perform well when there is a lot of noise in the data set, such as overlapping target classes. There will be a decrease in SVM performance if the number of features per data point exceeds the number of training samples.
[15]	Approaches using Genetic Algorithms	Genetic algorithms (GA) have been widely used in ECG analysis to gain higher computational capabilities with reduced time consumption.	Its mutation is unguided. The mutation operator in GA acts as a random number generator for mathematical optimization techniques and needs consumer time.

We will summarize the above-mentioned table with the following Table 6 that clarifies the most important meanings and details that the researcher must know before working:

Table 6: Summarize of Approaches ML [62]

Refers	Name	Supervisor	UN Supervisor	Sime-supervisor	Tim-consumer	Big data
[48]	FUZZY algorithm	√	⊠	⊠	⊠	√
[27]	RST algorithm	√	⊠	⊠	√	√
[5]	ANN algorithm	√	⊠	⊠	⊠	√
[44]	SVM algorithm	√	⊠	⊠	√	⊠
[15]	Genetic Algorithm	⊠	⊠	√	√	√

5.3. ECG in Deep Learning

As a non-invasive diagnostic technique, the electronic cardiogram or EKG is frequently employed. ECG data can be used to diagnose a number of cardiovascular disorders by tracking the heart's physiological activity over time. Premature atria contractions and other anomalies are common. There are many disorders that affect the heart, such as atrial fibrillation (AF), myocardial infarction (MI), and congestive heart failure (CHF) [2].

The medical sector has seen the rise of portable ECG monitors like the Holter monitor and wearable devices like the Apple Watch in the last few years. This has resulted in an increase in the number of ECG data that needs to be examined [8]. This has led to an increase in interest in ECG data processing. Biometric human identification and sleep staging may also be accomplished using ECG data. Human identification is a crucial step in ensuring the safety of data. One of the most promising ways is to build deep learning models for human identification from electrocardiogram (ECG) data [32].

Among its many advantages are its liveness detection, low sensitivity, ease of collecting, and increased security. Other methods rely on a classifier to detect closed sets, while matching-based methods require a lot of computing time [54]. It is crucial to uncover early indicators of cardiac disease, such as ECGs, because they are the most often utilized diagnostic tool. Health care innovation has recently been reinvigorated by the massive expansion of electronic health records, which includes the systematic collection and evaluation by machine learning and deep learning of various types of digitalized medical data, as well as new methods to efficiently evaluate this large amount of data [3].

Electrocardiogram (ECG) learning strategies are reviewed in this work, and the most well-known studies and technical papers on the issue are included. As illustrated in the bottom of Figure 1, deep learning approaches do not necessitate the use of human specialists to extract features from data 8. A deep learning model uses powerful data learning to automatically and implicitly extract features.

5.4. Typical realization of an ECG-based identification system

In an ECG-based identification system, there is a well-established procedure [25], as shown in Figure 9. As part of the process of registering a student, their unique traits are gathered and saved. All noise and artifacts are filtered out, and features are extracted and processed, during the enrollment process the identification process might begin when a few of people's traits have been documented [4].

The system is confronted with an unknown ECG during the identification procedure. In the same manner as enrollment, preprocessing and feature extraction/transformation are performed. As

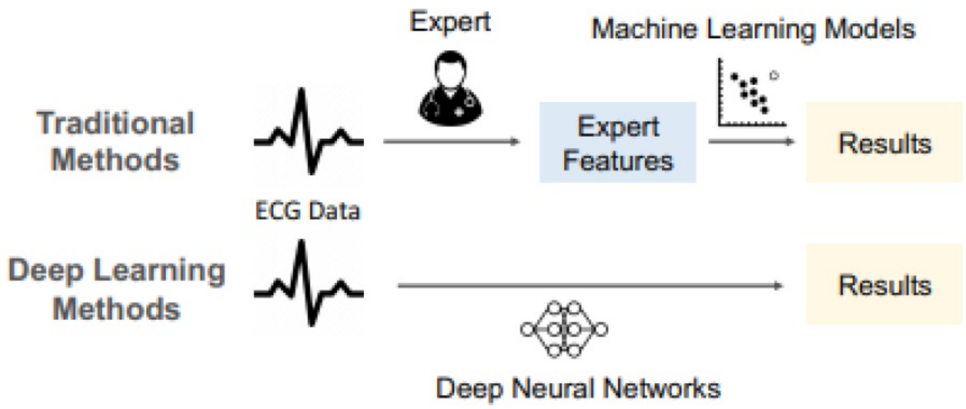


Figure 8: A comparison Between Traditional approaches and deep learning methods are compared [18].

a final step, a classification algorithm uses the collected features to match the database data to the best-matching topic (see "Classifiers"). An important part of attaining the best results in ECG identification is extracting, selecting and modifying ECG variables, as well as classifier structure [21]. The next paragraphs show ECG-based identification system:

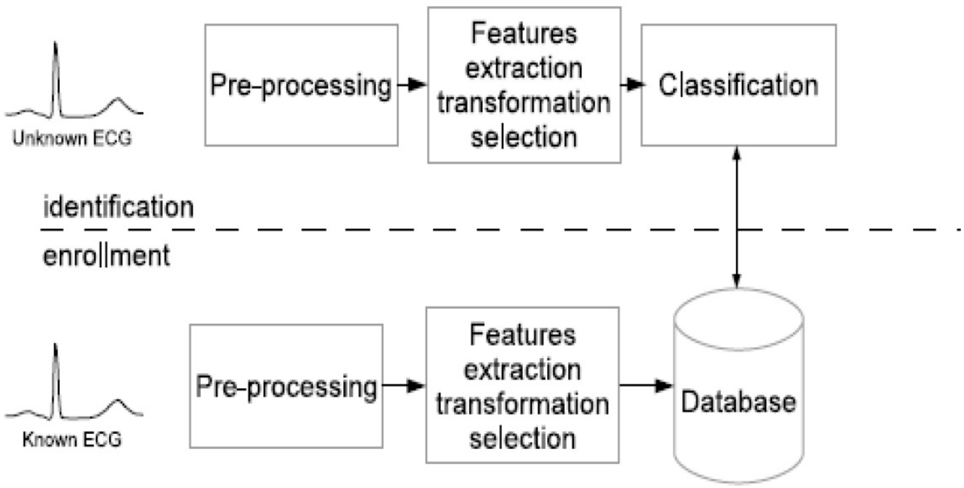


Figure 9: A typical ECG-based identifying system implementation [67].

5.5. ECG features

There are plethora of ECG-based recognition methods, each with its own set of advantages and disadvantages. The purpose of ECG properties (features) is to classify a single subject by taking advantage of inter-subject variability [70]. An ECG wave time interval or the shape of the heartbeat may all be utilized to establish a characteristic. If you need real-time identification, you'll need a more advanced recognizer. You'll need a particular recording device, and so on [60]. No one has come to a consensus on what the ideal method is or how many features to include. There are a number of factors that make it difficult to compare ECG analysis methods. Approaches based on fiducials are also being used in addition. Fiducial points or fiducials can be found on ECG recordings and utilized as inputs to recognizers for a wide range of features [18]. The peaks, boundaries, slopes, and other characteristics of a wave serve as fiducials. Adaptive thresholds can be used by detectors.

The retrieved characteristics of the Fourier synthesis wavelet transform are heavily influenced by the detection accuracy [65]. And the next Figure 10 shows the taxonomy of ECG:

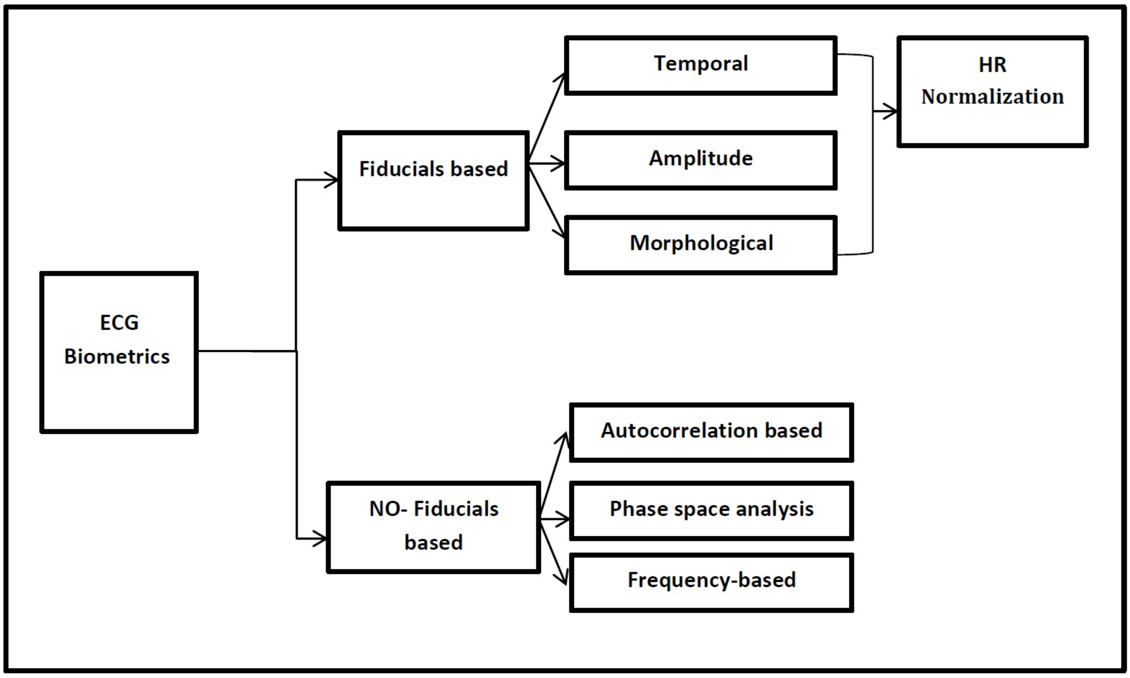


Figure 10: The taxonomy of ECG

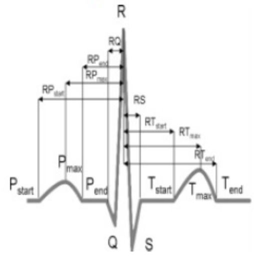
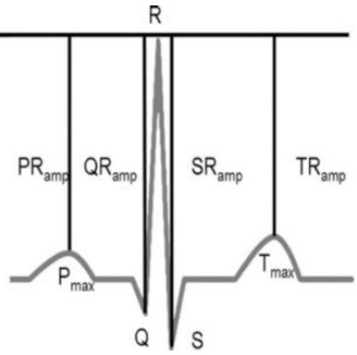
Fiducial-based approaches Fiducial points or fiducials can be found on ECG recordings and utilized as inputs to recognizers for a wide range of features [50]. The peaks, boundaries, slopes, and other characteristics of a wave serve as fiducials. Adaptive thresholds can be used by detectors. Other techniques, such as the Fourier synthesis wavelet transform and others, are described in Clearly, the precision of the detection has a significant impact on the extracted features. Researchers, on the other hand, have found ways to use fewer fiducials in some circumstances (often to the only R peak identification) Temporal, amplitude, and morphological characteristics can all be subdivided using fiducials. Authors routinely mix and match these aspects [56].

Recognized properties such as temporal, amplitude, and morphology need precise fiducial detection, and the results produced depend on that detection technique. The problem has been addressed with novel tactics that don't need the identification of fiducials. In all of the solutions outlined, the ECG is assumed to be a highly repetitive (quasi-periodic) signal. Following a survey of the scientific literature, we identified three types of methodologies: Analyses based on autocorrelation, phase space, and frequency [57]. In terms of definition, mathematical expression, and effort, we will explain these features in the following table 7:

6. Data

This data comes from the five most often used databases for evaluating work-related electrocardiograms. Databases from healthcare devices aren't as common as those from medical devices [10]. Medical device data often contains more leads than healthcare device data, which means that medical device data is more informative than healthcare device data [51]. Medical device data, on the other hand, is more difficult to get. Wearable ECG monitors are becoming more common in healthcare settings and have a higher lead count. ECG systems with 12 or 15 leads are more sensitive than

Table 7: Type of Features [42, 26]

Feature Name	Definition	explanation
Temporal	There is a temporal link between the different ECG waves P, QRS, and T, which may be utilized as biometric distinguishers, beginning with the sino-atrial node and ending with Purkinje fibers. Time intervals between heartbeat waves (i.e., P, QRS, and T) are the most often used temporal characteristics (PQ, RS, ST, etc.).	
Amplitude	An individual's heartbeat's amplitude varies from one person to another, and this variability is immediately recognized by the individual. It is important to note that when measuring the amplitude characteristics of an ECG wave, it is common to compare it to the R peak of the wave. If you want to know how loud your heartbeat is, you may measure the relative amplitude of each ST segment, as well as the peaks of the first and second derivative pulse waves and their corresponding amplitude ratios.	
Morphological	ECG morphological features are the ones that tell us about how it looks as a whole or how particular intervals fit together (P-QRS-T). To extract morphological information from the pulse, one may simply average the observed values of particular intervals (e.g., QRS) over several heartbeats that are aligned (i.e., R peak). The following equation describes the QRS form factor (FF), which is used to explain amplitude.	FF= $\sqrt{\frac{Var(X')/VAR(X)}{Var(\acute{x})/Var(X)}}$ Where: X= QRS complex waveform X'= is the first derivative of the QRS X''= is its second derivative.
Autocorrelation based	It is insensitive to shifts and draws attention to non-random patterns. This is especially true for the QRS complex, which maintains a high amount of shape and time-width invariance. In contrast to conventional methods, this method enables for the detection of fiducials in samples that would otherwise be adversely affected by the presence of fiducials.	$r[m]=\frac{1}{r\|0\|}\sum s[i]\, s[i+m]$ Where: $r[m]$ = the AC $s[i]$ = the signal at time i and m is chosen greater than the mean QRS duration (in samples)
Phase space analysis	ECG signals can be defined in two- or three-dimensional space using the time delay approach, depending on the application. For the first time, it is feasible to identify previously unknown aspects of the heart's activity using three-dimensional single-lead time-delayed (4–36 ms), amplitude normalized ECGs.	**(s(t), s(t+dt), s(t+2dt)).** By partitioning the phase-space into a 30 × 30 grid, the multi-loop trajectory is reduced to a coarse-grained features space, minimizing computational cost and loop variability due to noise or ECG irregularity.
Frequency-based	Using a linear predictive model, the frequency content of ECG data was modeled (linear predictive coding, or LPC). First forty points of the ECG's linear reconstruction are combined with the first forty points of the ECG's linear reconstruction to create the spectrum model for each subject.	$\hat{x}[n] = -\sum_{i=1}^{p} aix[n-1]$ where the ai coefficients are evaluated by minimizing the error e[n] where: $e[n] = x[n] - \hat{x}[n]$ Where x[n] =the actual value.

single-lead ECG systems, which are more sensitive than single-lead ECG systems (similar to lead I in a 12-lead ECG) [34]. Table 8 provides an explanation:

Table 8: Description of Famed Data

RE	Name of data	Description of data
[38]	MIT-BIH Arrhythmia Database	The study consists of 48 half-hour ECG recordings taken from 47 patients at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Center). There are 11-bit resolutions of 10 mV and 360 Hz for each ECG data series. The beat and rhythm levels of this dataset are carefully annotated with diagnoses.
[12]	The PhysioNet Computing in Cardiology Challenge 2017 dataset	In total, there are 8,528 de-identified ECG recordings recorded at 300 Hz by an AliveCor healthcare device, with recording periods ranging from 9 seconds to slightly more than 60 seconds. Over half (51,154) of these recordings are in perfect condition. In addition to 717 AF recordings, there are 2,557 additional recordings. In 46 of the recordings, there is nothing except background noise. In addition, 3,658 recordings of the tests are kept confidential for scoring purposes. Medical gadgets collected this data.
[6]	The PTB Diagnostic ECG Database	There is 549 (15-channel ECG data from 290 people in this collection. The sampling rate can go up to 10 kHz. There are 216 people with one of eight types of heart disease, 52 people who are in good health, and 22 people who aren't sure.
[37]	The MIT-BIH Atrial Fibrillation Database	The collection includes 25 10-hour long-term 2 lead ECG recordings of human AF patients at a sampling rate of 250 Hz" (mostly paroxysmal). The PhysioNet Computing in Cardiology Challenge 2017 dataset was used to evaluate deep learning algorithms at Beth Israel Hospital in Boston. There are no ways in the concealed test set that do not have a score of at least 0.8.
[31]	2018 The China Physiological Signal Challenge dataset	Recordings ranging from six to more than 60 seconds long were taken from 11 universities at a sample rate of 500 Hz and included in the database. Recordings include 918 "normal," 1,098 "AF," 704 "first-degree atrioventricular block," 207 "left bundle branch block," 1,695 "right bundle branch block," 556 "pac," 672 "PVC," 825 "ST-segment depression," and 202 "ST-segment elevation" ones. Additionally, a password is required to access 2,954 test recordings for scoring.

The following is a table showing the most important characteristics of these databases in table 9:

Table 9: Characteristics of Database [42, 26]

database	Records	Leads	Duration	Year
MIT-BIH Arrhythmia Database	47	2	30 minutes	1975-1979
The PhysioNet Computing in Cardiology Challenge 2017 dataset	8528 train, 3658 test	1	30 seconds	2017
The PTB Diagnostic ECG Database	549	15	Several minutes	1995
The MIT-BIH Atrial Fibrillation Database	25	2	10 hours	1983
2018 The China Physiological Signal Challenge dataset	6877 train, 2954 test	12	15 second	2018

7. Previse Studies in ECG

Many studies have been conducted on the subject of electrocardiogram, and they were divided into two methods: the first method is the detection of diseases, and the second method is security and identification of people through the immutable ECG, which is considered safer than the rest of the other techniques [40]. The following is a table 10 showing these studies:

Table 10: Previous Studies in ECG

Ref.	Year	Method	Contribution	Limitation	Dataset
[22]	2015	Gaussian kernel-based SVM for comparing data	A multitask learning strategy combines the extraction of features with the construction of classifiers. The kernel of each job is assigned a certain set of weights.	Not put to good use. In multitask learning, feature extraction and classifier construction are performed simultaneously on all binary classification tasks.	MIT-BIH Normal Sinus Rhythm database from PhysioNet.
[20]	2016	A approach that combines support vector machines and radial basis functions.	the AAMI defines five unique arrhythmia beat classes: non-ectopic (N), supraventricular (S), ventriculoendothelial, or "fusion," or "timed," beats, and unclassifiable and timed. This study looked at all five of these distinct arrhythmic beat classes (U). For example, the principal component analysis of discrete wavelet transform coefficients provides a characterisation capability by combining nonlinear characteristics such as high order statistics and cumulants, as well as nonlinear feature reduction approaches such as independent component analysis. A variety of classifiers are used to evaluate the features' ability to discriminate between different types of data.	He did not mention the percentage of database usage or the evaluation method	MIT-BIH
[24]	2017	Fuzzy algorithm and PCA redaction	The cluster partitioning of ECG feature data is proposed using an unique fuzzy-entropy-based c-means clustering (FECM). As a result, two entropy-based techniques for dimensionality reduction and clustering have been presented to enable automatic feature detection in ECG data.	They do not alter EPCA or FECM in order to accommodate dynamic ECG signals obtained from remote cardiac devices.	MIT-BIH Arrhythmia Database
[17]	2018	The 12-lead ECG readings are used to identify individuals.	A method of building one's identity is the primary goal. ECG signals are utilized to extract a new feature termed dynamics, which is then employed for identity identification, or alternatively, an ECG-based method for identity recognition via deterministic learning is presented. An individual's identity is established by analyzing the ECG signal's dynamics.	Because the dataset was compiled manually, the findings evaluation and comparison to previous work are incorrect, as the dataset contains no responses.	The Specialists used the suggested methods to get ECG recordings from the PTB diagnostic ECG database for testing.

[18]	2019	CNN	Deep-ECG, a biometric approach for ECG signals based on CNNs, is introduced by the authors. This is the first time a CNN has been used for biometric ECG analysis, to our knowledge. For identification, verification, and periodic re-authentication, Deep-ECG uses a deep convolutional neural network to gather important features from one or more leads and compares biometric templates using simple and quick distance functions.	develop more complicated topics that allow for greater recognition accuracy. Deep-ECG binary features for template protection implementation should also be examined in greater depth.	used two datasets for training and one for testing named DB-H-S and DB-H-L. These three datasets were created manually based on E-HOL-03-0202-003.
[25]	2020	Deep ECG encoder The and d encoder	presented CardioID as a solution to the aforementioned issues. Continuous ECG data is used to train CardioID to recognize binary codes that can be identified more quickly than other approaches. In addition, it may be used to identify new people without having to re-train the model. Another advantage of introducing statistical hypothesis testing is that it can theoretically ensure recognition accuracy.	Other physiological signals, such as an electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), and so on, were not examined. CRediT	real-world ECG data from PhysioNet Challenge 2017 databases
[68]	2021	CNN	There are no sophisticated model computations to deal with, therefore the proposed approach is faster and more effective even if only a limited amount of training data exists. The 1200 ECG recordings collected from 600 individuals were used to examine five hypothetical but potentially real-world scenarios.	without focusing on other ways to feed deep learning models, such extracting a spectrogram and enhancing accuracy and recognition speed by doing so, for example. More significant, however, is the point.	selected 3 datasets from the PhysioNet ECG

8. Conclusion

The ECG measures the heart's electrical activity. Its vitality properties make it a possible alternative to conventional biometrics for use other than medical diagnosis. Throughout this paper, we have presented a survey on the concept of electrocardiogram from both the medical and security perspectives, as well as a method of comparison between the different types of identification methods available for this type of identification and what the advantages and disadvantages of each are. During the time period 2015-2021, that is, the last six years, there have been several significant or influential studies on this issue.

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