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AN ANALYTICAL STUDY ON THE MOST IMPORTANT METHODS AND DATA SETS USED TO IDENTIFY PEOPLE THROUGH ECG: REVIEW

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ABSTRACT
The electrocardiogram is a topic of great importance from a medical and biometric perspective, especially recently, as researchers have begun to search for new biometric methods other than the palm print, fingerprint, or iris as alternative systems. Researchers discovered that ECG has unique features that are not common among humans, making it a good topic for researchers in biometric systems for identifying people. In this research paper, the goal is to shed light on the most important basic concepts that are related to ECG in terms of the methods used by researchers and in terms of the most critical data sets used by researchers, and also to shed light on some previous studies that achieved a high rate of citations, and also to shed light on the most important basic concepts that make Its features are unique and intelligence methods can be used effectively.
Keywords: *Electrocardiogram, Biometric, Medical, Methods, Dataset, Intelligence*

1. Introduction

The ECG signal is presently employed in several clinical applications that examine the waveform's morphology and temporal characteristics. These applications include diagnosing cardiac illnesses, remote patient monitoring, telemedicine services, arrhythmia detection, heart rate monitoring, congestive heart failure identification, and critical care unit patient monitoring. Aside from its clinical applications, the electrocardiogram (ECG) is also employed for human biometric identification (Ibrahim et al., 2022). This application, unrelated to clinical settings, has received significant attention from the scientific community involved in developing expert and intelligent systems. Recognition systems are currently used in many practical applications to protect personal security and confidential data. Although some systems use traditional technology such as cards, keys, or passwords, these mechanisms typically have issues with both ease of use and security (Sandau et al., 2017)(Abed et al., 2023). As a result, there has been a significant increase in the level of interest in biometrics. Biometric recognition refers to using unique physical and behavioural traits to verify people's identities automatically (Sandau et al., 2017) (AlMusallam & Soudani, 2021) . The former include facial features, fingerprints, iris patterns, and hand morphology, while the latter can refer to gait cues and keystrokes. Scientists have recently begun investigating the possibility of using ECG pulses as a separate biometric identity due to their unique properties: (1) Life detection: ECG can detect ECG signals only from Alive individuals, as it picks up electrical signals. Heart activity. (2) Enhanced security: ECG signals show a high resilience to counterfeiting, making it impossible to generate fake signals using the technology. (3) Analysis of ECG data provides vital information about an individual's identity, cardiovascular problems and general mental and physical condition (Sadiq & Mahmood, 2014). Electrocardiographic signals exhibit individual specificity due to differences in ionic potentials, plasma electrolyte concentrations, and physiological variations arising from chest geometry, volume, and heart position differences. Researchers have recently demonstrated that an electrocardiogram (ECG) can serve as a unique and confidential biometric (Ansari et al., 2017; Salerno et al., 2003).

2. ECG signal details

An electrocardiogram (ECG) to evaluate the heart's performance has been widely used recently. The device aims primarily to accurately measure the frequency of heart contractions (heart rate) and the consistency of heart contractions (heart rhythm) (Teferra et al., 2019). ECG can provide essential data, such as possible constriction of the coronary arteries, myocardial infarction, or abnormal heart rhythm, such as atrial fibrillation, clearly and accurately (Rahma & Salman, 2022). The heart generates a characteristic electrocardiogram (ECG) pattern while maintaining a constant rhythm (Charlton et al., 2018) . There are fixed divisions of the ECG where the P wave indicates the propagation of the electrical impulse or stimulus through the atria in the heart. The atria contract, pushing blood into the ventricles, and then quickly relax. Then, the electrical impulse spreads to the ventricles. The Q, R, and S waves in the electrocardiogram (ECG) signify the presence of the QRS complex. Ventricular contraction takes place (Nakano et al., 2021). The T wave signifies the termination of the electrical impulse transmission, resulting in the relaxation of the ventricles. Electrocardiograms (ECGs) can diagnose cardiac diseases and irregular heart rhythms (arrhythmias) (Marinho et al., 2019). By scrutinizing their physical characteristics and the progression of their growth, one can aid in pinpointing the underlying origins. Figure 1 displays the specific characteristics of the ECG signal (Attia et al., 2021).

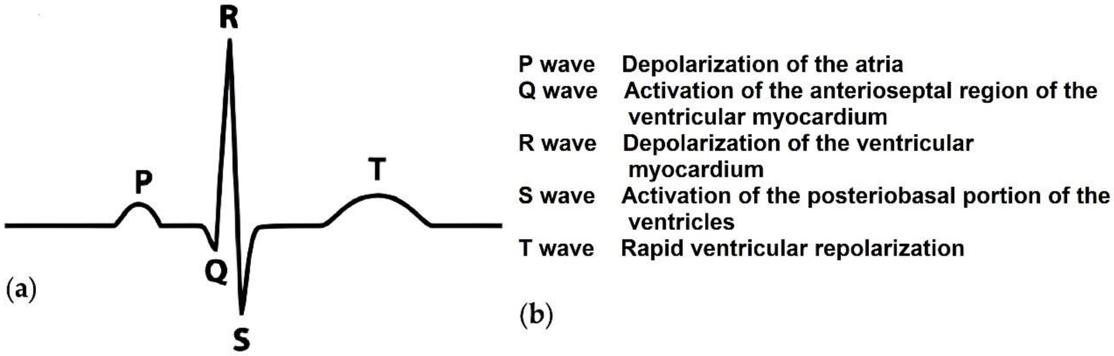

Fig. 1. Ideal electrocardiogram (ECG) signal with significant features: (a) P wave, QRS complex, and T wave, which help diagnose heart signal abnormalities; (b) ECG signal features—how and where the heart creates them.

3. Biometrics

"biometrics" comes from "automated recognition of individuals based on their behavioural and biological characteristics." This definition comes from the "International Organization for Standardization"(Ibrahim et al., 2022). They are a part of our everyday lives in some capacity, serving either as a means of personal identity or validation. By using biometric authentication, the system can confirm a person's claimed identification, whereas, in the biometric identification process, the system determines how the individual is without needing that individual to have first claimed an identity (Pal et al., 2015). As examples of biometric qualities, some distinguishing characteristics that have been used include fingerprints, faces, irises, hand geometries, voices, signatures, and gaits. Recently, ECG has been suggested as a candidate for use as a biometric feature because its information is both hidden and inherently live (Shkara & Hussain, 2018). In addition, ECG is said to be unique to each individual and varies from that of other people, making it possible to differentiate between various people(Sansone et al., 2013). The vast majority of the already available research focused on demonstrating that an ECG is capable of functioning as a biometric by outlining the various qualities that should be included in such a feature (Yen & Francisco, 1990)(Salloum & Kuo, 2017) :

- **Uniqueness:** Because of its uniquely individual characteristics, electrocardiograms are suitable for use in advanced identity verification systems.
- **Stability:** To provide evidence of consistency, it is necessary to Collect data from the same individual over a sufficient period.
- **Collectability:** Electrodes are now only required to be placed on the chest for modern ECG recording equipment, making the process much less intrusive than in the past. In addition, some methods do not involve the person being scanned to acquire signals from the hands, wrists or fingers.
- **Performance:** Several variables influence the efficiency of a biometric system, including how the signal is acquired, the degree to which the signal is of high quality, the

preprocessing techniques, including the attributes that are selected, the template that is applied, and the matching algorithm.

- **Acceptability:** There has been an increase in options to develop biometric systems based on ECG that are less invasive and, as a result, increasingly acceptable in social settings since the development of dependable ECG devices that only require a limited amount of invasiveness.
- **Circumvention:** There has been a rise in the number of possibilities for the development of ECG-based biometric systems that are less invasive, and as a direct consequence of this, there has also been an increase in the number of, given the introduction of reliable ECG technologies that only require a minimum amount of invasiveness, it has become more socially acceptable.

Figure 2 summarises the main point of using the feature ECG.

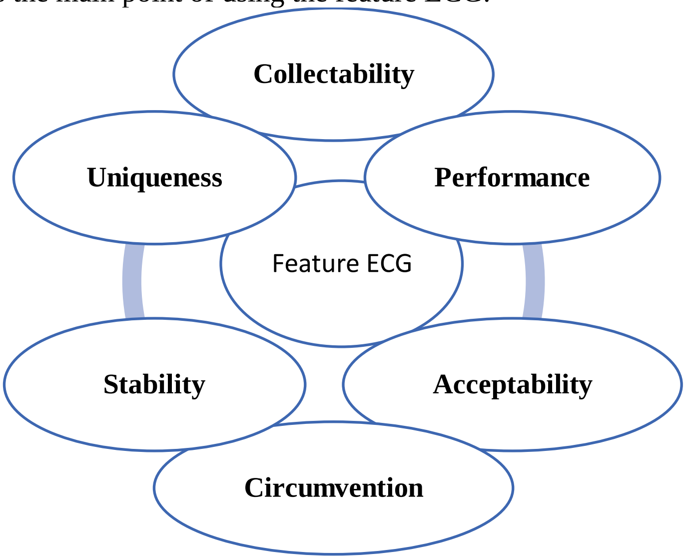

Fig. 2. The ECG Signal Feature Provided In The Biometric Topic.

4. ECG System Identifying

Identifying individuals includes signal preprocessing, feature extraction, and classification. Because the physiological and geometrical shapes of people's hearts, reflected in their electrocardiogram (ECG) impulses, are unique, this biometric characteristic is essential for human identification. (Odinaka et al., 2012). ECG signals represent Recordings of the heart's electrical activity (Man et al., 2015). A general distinction can be made between the phases of polarization and repolarization. Depolarization phases include the P-wave and the QRS-wave in an electrocardiogram. The repolarization stages in the T-wave can be observed (Yang et al., 2015). Figure (3) shows the general structure of the ECG identification system. Table 1detailed the differences between ECG biometric and others ways of identifying humans.

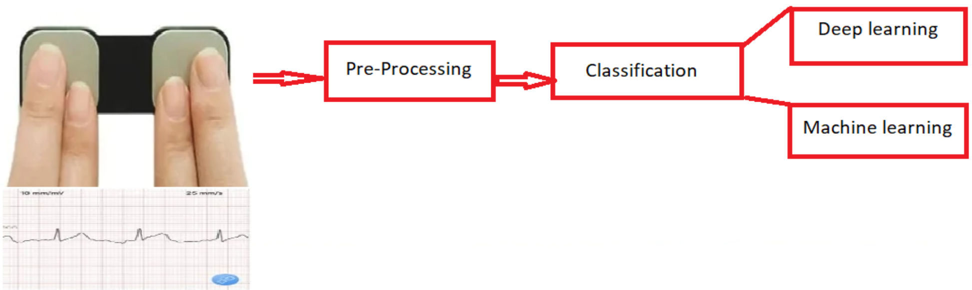

Fig. 3. General Diagram of The ECG identification system (Merone et al., 2017).

Table 1 - summarizes the differences between ECG biometrics and other identifying systems.

Feature	ECG	Iris Recognition	Fingerprint Scanners	Palm Print Recognition
Accuracy	High	Very high	High	High

Convenience	Less convenient (needs electrodes)	Requires specialized cameras	Easy to use (integrated into several devices)	Quite practical (scanners are not as common)
Privacy considerations	Some may have concerns about keeping ECG data	Less of a worry	Less reason for alarm	Less reason for alarm
Liveness detection	inherent (needs a working heart)	Can be implemented with extra tests (for example, blinking)	No (further investigation required)	No (further investigation required)
Error susceptibility	May be influenced by cardiac issues	Contact lenses or eye disorders might alter readings	dirt or fingerprint damage	Moisture, grime, or scars
Tamper-proof	Relatively tamper-proof (ECG is difficult to fabricate)	High (difficult to create iris patterns)	Less tamper-proof (potential high-quality copies)	Reduced tamper-proofness (prone to forgeries)
Cost of equipment	Generally more expensive (specialised equipment)	Can be pricey (specialist camera)	Less expensive (generally accessible)	reasonably priced (scanners are less prevalent)
Ease of Use	requires user involvement (placement of electrodes)	requires user cooperation (looking at camera)	Ease of use (just place your finger there)	requires user assistance (hand placement)
Type of measurement	Electrical activity of the heart	Patterns in the colored portion of the eye (iris)	Fingerprint ridges and troughs	The palm's creases, lines, and patterns

5. Roles of Artificial Intelligence in ECG

Electrocardiography (ECG) increasingly uses AI for diagnosis, classification, and management. AI algorithms help clinicians: (1) interpret and detect arrhythmias, ST-segment changes, QT interval prolongation, and other ECG abnormalities; (2) integrated risk prediction with or without clinical variables to predict arrhythmia, sudden cardiac death, stroke, and other cardiovascular events; and (3) monitoring ECG signals from cardiac implantable electrical devices and wearable devices in real-time and alerting doctors or patients of significant changes. (4) Treatment guidance, patient selection, optimization, symptom time to treatment, cost-effectiveness (early reactivation of coronary infarction in patients with ST-segment elevation, prediction of response to antiarrhythmic drugs or cardiac implantable device therapies, reduction of cardiotoxicity, etc.); (5). Facilitate integration of ECG data with other modalities. As more data and complex algorithms are generated, artificial intelligence will become more significant in ECG diagnosis and management (Mappangara et al., 2020)(Sarkar & Etemad, 2020)(Yousiaf & Al-Tamimi, 2023). Use biometric systems to authenticate and reveal identities. Artificial intelligence (AI) is a computer model that makes decisions using prior information and improves performance with experience (Cluitmans et al., 2018). In the current manuscript, AI is used as a synonym for (deep) machine learning (algorithms) (hybrid) convolutional neural networks. Artificial intelligence (AI) is revolutionizing the field of electrocardiography (ECG) in many ways, providing significant benefits to healthcare professionals and patients. Here are some of the critical roles that AI plays in ECG (Fratini et al., 2015; Y. Sun et al., 2005):

- Diagnosis and interpretation, i.e. improved accuracy: Artificial intelligence algorithms can analyze ECGs with high accuracy, exceeding human performance in detecting subtle abnormalities. This helps in early diagnosis of various heart conditions, including arrhythmia, myocardial infarction, and cardiomyopathy.
- Reduce inter-observer variability: Different doctors can interpret the same EKG differently, leading to potential misdiagnoses. AI algorithms provide consistency and reduce variability in interpretation, improving diagnostic confidence.
- Automated analysis and reporting: Artificial intelligence can automatically analyze ECGs, saving a doctor's time and resources for patient care. It can also generate detailed reports with annotations, highlighting potential areas of interest.

- Improve Biometric systems: Artificial intelligence can build biometric systems dedicated to detecting people or identifying them efficiently through deep learning, machine learning algorithms, and pre-trained models.

Figure 4 summarises all the points above about AI's roles in ECG.

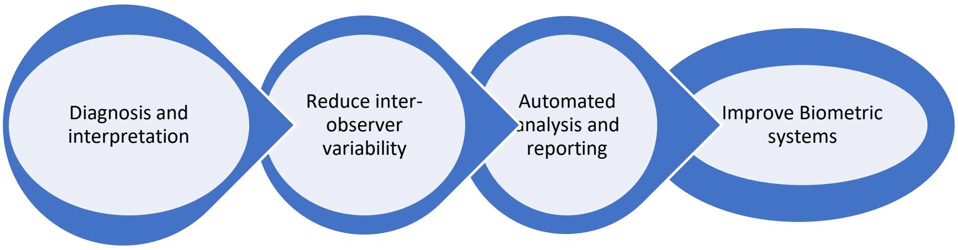

Fig. 4. AI's roles in ECG.

The table 2 summarizes several important discoveries and new developments in the field of ECG-based biometric identification:

Table 2 - Provides An Overview Of A Number Of Significant Findings And Recent Advancements In The Field Of ECG-Based Biometric Identification.

Aspect	Key Findings	Emerging Trends
Uniqueness of ECG	- ECG signals provide a unique biometric identifier due to anatomical and physiological differences.	- Investigation of combining ECG with other biometrics (multimodal) to improve security.
Security	- ECG is difficult to fabricate since it represents the electrical activity of a living heart.	- Developing spoofing detection algorithms to mitigate potential issues.
Signal Processing	- Wavelet transform and feature extraction techniques help to increase ECG identification accuracy.	- Using deep learning algorithms (CNNs and LSTMs) for ECG analysis.
Classification Algorithms	- Existing methods are based on extracting certain traits and comparing them to a database.	- Investigate non-fiducial approaches for analyzing larger signal patterns.
Applications	- ECG provides liveness detecting capabilities for secure systems.	- Investigating ECG-based identification in many sectors, including healthcare access control and mobile banking.

6. Methods of AI

Learning algorithms are the fundamental basis of artificial intelligence, enabling computers to acquire knowledge from data and enhance their performance progressively (Abd-Alzhra & Al-Tamimi, 2022). These algorithms analyze extensive data sets, detect patterns and correlations, and generate predictions based on their discoveries (Yen & Francisco, 1990). The subsequent diagram provides a concise overview of their categorization and classifications in Figure 5.

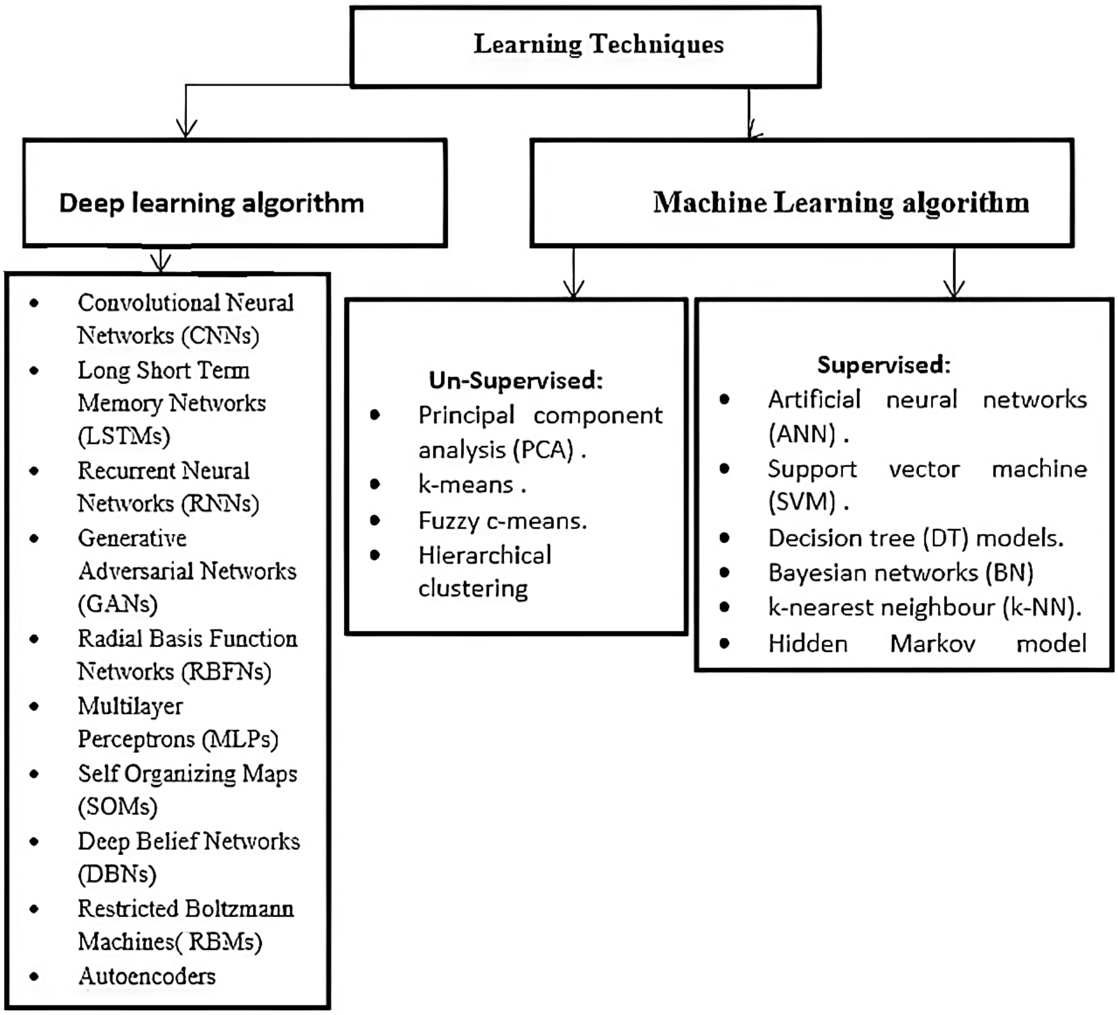

Fig 5. Famous learning algorithms (AL-Jibory, Farah K, 2021; Sabeeh & Khaled, 2021).

Artificial intelligence encompasses various methodologies and strategies, each with advantages and disadvantages (Al-Tamimi, 2019). Several notable techniques include:

- Machine learning is a specialized branch of artificial intelligence (AI) that deals explicitly with developing algorithms capable of acquiring knowledge and improving performance via data analysis; in recent times, generative artificial neural networks have demonstrated superior performance compared to numerous prior methods (Al-Juboori, 2017). Machine learning techniques have been utilized in several domains, such as substantial language models, computer vision, speech recognition, email filtering, agriculture, and medicine. This is particularly beneficial when developing specific algorithms for performing required tasks is prohibitively expensive (Bassiouni et al., 2018; Sullivan, 2020). The following Table 3 summarises the Benefits of Machine Learning, and Table 4 summarizes the algorithms used in the ECG biometric system.

Table 3 - summarizes the Benefits of Machine Learning (Bi et al., 2019; *Methods and Studies for Human Electrocardiogram : A Survey*, n.d.)

Benefit	Description	Example
Automated decision making	Replaces time-consuming and error-prone tasks with AI-driven predictions.	Fraud detection, credit risk prediction, churn prediction
Improved accuracy	Often achieves higher accuracy than human decision-making, especially for complex tasks.	Disease diagnosis, patient outcome prediction, personalized treatment plans
Personalization	Tailors experience individual users based on their preferences and behaviour.	Product recommendations, content suggestions, personalized advertising

Scalability	Easily handles large datasets and complex problems with high computational efficiency.	Traffic flow optimization, demand prediction, inventory management
Enhanced efficiency	Automates repetitive tasks and optimizes workflows, saving time and resources.	Customer service automation, data analysis and processing, anomaly detection
Data-driven insights	Uncovers hidden patterns and trends in data, leading to better decision-making.	Market research, customer segmentation, product development
Improved prediction	Makes accurate predictions based on historical data, enabling proactive measures.	Weather forecasting, stock market trends, maintenance scheduling
Cost reduction	Automates tasks and optimizes processes, leading to cost savings.	Fraud prevention, resource allocation, predictive maintenance
New product and service development	Enables the development of innovative products and services based on customer insights.	Personalized learning platforms, intelligent assistants, customized healthcare plans

Table 4 - summarises algorithms used in the ECG biometric system (Dey, 2016)

Algorithm	**Function**	**Benefits**
Signal Preprocessing:	- Denoising: Removes noise from the ECG signal.	- Improves data quality and accuracy.
- Baseline Correction: Removes baseline wander from the ECG signal.	- Improves signal clarity and feature extraction.	- Valuable information can be removed if not done correctly.
- QRS Detection: Identifies QRS complexes in the ECG signal.	- Provides key landmarks for feature extraction and analysis.	- Can be inaccurate for noisy or abnormal ECGs.
Feature Extraction:	- Extract relevant features from the ECG signal, such as QRS amplitudes, durations, and intervals.	- Reduces data dimensionality and simplifies processing.
- Time-domain features: Based on timings and intervals between ECG waves.	- Simple and efficient to compute.	- Limited information captured.
- Frequency-domain features: Based on the frequency spectrum of the ECG signal.	- Captures information about signal components and rhythms.	- More computationally expensive.
- Wavelet-domain features: Based on the wavelet transform of the ECG signal.	- Captures information about signal components at different scales.	- Requires careful selection of wavelet functions and parameters.
Matching and Classification:	- Compares extracted features from the test ECG to reference data.	- Identifies the subject based on similarity scores.

- Euclidean distance: A simple distance measure between two sets of features.	- Easy to implement and understand.	- Sensitive to outliers and feature scaling.
- Support Vector Machines (SVM): A robust algorithm for classification.	- Highly effective for high-dimensional data and non-linear relationships.	- Requires careful parameter tuning for optimal performance.
- Neural Networks: Can learn complex patterns and relationships in the data.	- Highly adaptable and can be trained on large datasets.	- Can be computationally expensive and prone to overfitting.

7. Deep learning

Deep learning, a subset of machine learning, has significantly transformed the area of artificial intelligence in recent times(M. S. Al-Tamimi, 2019). It draws inspiration from the organization and operation of the human brain, employing artificial neural networks with numerous layers to acquire intricate patterns from data. Envision an intricate labyrinth with concealed passages and numerous points of egress. Deep learning algorithms might be likened to astute navigators, adeptly traversing a complex network of interconnected nodes (Sun et al., 2021). Every layer in the system analyzes the data it receives from the preceding layer, extracting more complex and sophisticated features and patterns. This enables the model to acquire complex associations within the data, ultimately resulting in precise predictions or classifications (Kumar & Sathish Kumar, 2022)(Al-Khafaji & Al-Tamimi, 2022). The following Table 5 summarises the algorithm of DL used in ECG biometrics.

Table 5 - summarises the DL algorithm used in ECG biometrics (Gu et al., 2022; Janiesch et al., 2021)

Algorithm	**Function**	**Benefits**	**Challenges**
Convolutional Neural Networks (CNNs)	- Extract spatial features from ECG signals. - Identify patterns across leads and time.	- High accuracy in QRS detection, arrhythmia classification, and biometric identification. - Robust to noise and variations in ECG morphology.	- Requires large datasets for practical training. - Interpretation of learned features can be difficult.
Recurrent Neural Networks (RNNs)	- Model temporal dynamics of ECG signals. - Analyze sequences of ECG beats for rhythm recognition and anomaly detection.	- Can handle long-term dependencies in data, valid for analyzing heart rate variability and atrial fibrillation. - Effective for personalized ECG analysis based on individual patterns.	- Prone to vanishing gradients, making training for long sequences challenging. - Sensitive to noise and missing data.
Transformers:	- Encode and process ECG signals as sequences of tokens. - Capture long-range dependencies and context within the signal.	- Promising for multi-lead analysis, arrhythmia classification, and inter -patient similarity comparison. - May be more efficient than RNNs for handling long sequences.	- Requires specialized data preprocessing and attention mechanisms. - Still under active research and development.

Deep Autoencoders (DAEs)	- Learn compressed representations of ECG signals for anomaly detection and feature extraction.	- Can identify subtle changes and outliers in the data. - Useful for dimensionality reduction and data compression.	- Requires careful parameter tuning to avoid overfitting or underfitting. - Reconstruction errors may not be readily interpretable.
Generative Adversarial Networks (GANs)	- Generate synthetic ECG signals for data augmentation and training. - Can create realistic and diverse data for improving model performance.	- Can be used to address data scarcity issues. - Requires careful design and training to avoid generating unrealistic or biased data.	-Despite the remarkable proficiency of Generative Adversarial Networks (GANs) in producing authentic and imaginative data, they still encounter various obstacles that impede their broader acceptance and practical utilization.

Table 6 shows that Deep learning models such as U-Net, VGG, and EfficientNet have significantly transformed multiple domains, including image identification, natural language processing, and healthcare.

Table 6. summarized of the pre-training model in DL.

Model	**Description**	**Strengths**	**Weaknesses**
U-Net (Hwang et al., 2019)	A CNN architecture specifically developed to segment biological images. The system's topology is U-shaped, consisting of routes for encoding and decoding. This design enables accurate localization and extraction of features.	- Excellent for medical image segmentation tasks like tumour detection and organ identification. - Efficiently handles small datasets.	- Can be computationally expensive for large images . - Requires careful parameter tuning for optimal performance.
VGG (He et al., 2016)	A lineage of Convolutional Neural Network (CNN) structures is renowned for their uncomplicated nature and remarkable proficiency in task-categorizing images. The system consists of several consecutive convolutional layers, each utilizing tiny filters.	- Highly accurate for image classification, especially with ImageNet datasets. - Relatively lightweight and computationally efficient.	- May require large amounts of training data for optimal performance. - Prone to overfitting for small datasets.
EfficientNet (Alduwaile & Islam, 2021)	A family of CNN architectures optimized for both accuracy and computational efficiency. It scales the model size based on a predetermined formula, balancing performance and resource usage.	- Achieves state-of-the-art accuracy on image classification tasks while significantly smaller and faster than other models. - Well-suited for deployment on mobile devices or resource-constrained environments.	- Necessitates particular training methodologies due to its intricate structure. - It may not be as effective for all image classification tasks as specialized models.

8. Famous dataset in ECG

In ECG biometrics, a dataset is a compilation of electrocardiogram (ECG) recordings utilized for training and assessing biometric identification and authentication systems. The usual contents of these recordings encompass(Hameed & Al-tuwaijari, 2022; khiled AL-Jibory et al., 2022):

- Data points refer to the unprocessed electrical impulses obtained from the heart using electrodes on the body's surface. These signals are commonly depicted as voltage readings over some time.
- Annotations refer to supplementary data linked to each ECG recording, including:
- Demographic characteristics of the subjects include age, gender, height, weight, and other relevant factors.
- ECG lead information refers to the electrodes utilized for recording, such as Lead I, Lead II, etc.
- Signal quality refers to the cleanliness of a recording and if it contains any unwanted noise or artefacts.
- Biometric identifiers refer to distinct characteristics derived from the ECG signal employed for identification. These characteristics include QRS amplitudes, durations, and intervals.
- Ground truth labels refer to the verified identity of the individual connected to the recording.

A dataset in ECG biometrics is a collection of ECG recordings used to design and evaluate biometric identification and authentication systems. The following are the standard recording elements:

→ **ECG Signals:** The core element, the ECG signals themselves. These represent the electrical activity of the heart, captured by electrodes placed on the chest or limbs.
→ **Metadata:** Information associated with the ECG recordings, such as:
→ **Subject Demographics**: Age, gender, height, weight, etc.
→ **Recording Conditions:** Resting state, physical activity, medications taken, etc.
→ **Device Information:** Type of ECG device used, sampling rate, electrode placement details.
→ **Labels**: In identification scenarios, labels might indicate the identity of the individual the ECG recording belongs to. In authentication, labels could be a simple "genuine" or "imposter" classification.

The following table 5 summarized the best dataset that using in ECG biometric based in previse studies of researcher.

Table 7 summarizes the best dataset in ECG using in-topic biometrics.

Table 7 - dataset in ECG using in-topic biometrics (Merone et al., 2017)(Hameed & Al-tuwaijari, 2022)

Dataset	Description	Strengths	Weaknesses	Link
PhysioNet Challenge 2012 (CPSC2012)	Contains recordings from 38,103 patients, including various ECG abnormalities and noise sources.	Large size and diversity, good for abnormality detection and classification tasks.	Limited annotations for specific beat types may require further processing.	https://physionet.org/content/challenge-2020/
MIT-BIH ECG Database	Contains recordings from 48 healthy volunteers and 232 patients with various arrhythmias.	Well-annotated with beat labels and diagnosis information, suitable for rhythm analysis and diagnosis tasks.	Compared to others, a relatively small size may not be suitable for large-scale studies.	https://physionet.org/about/database/
PTB-XL	A large public dataset of 188,699 ECGs from 10-second recordings of 18,869 patients, with diverse diagnoses and annotations.	Enormous size and diverse diagnoses, suitable for large-scale studies and deep learning models.	Due to limited ECG lead availability (Lead II only), annotations may not be perfect for all cases.	https://pubmed.ncbi.nlm.nih.gov/32451379/
ECG-TU-Hamburg	Contains recordings from 78 healthy volunteers and 153 patients with various	Detailed beat-level annotations are suitable for rhythm analysis and beat	Relatively small compared to others, limited ECG lead availability	https://physionet.org/content/ptbdb/

	arrhythmias, segmented into individual beats for detailed analysis.	classification tasks.	(single lead).	
St. Petersburg Institute of Cardiology (SPIC) Database	Contains recordings from 30,000 patients with diverse cardiovascular diseases, including ECGs and other clinical data.	Rich clinical data and diagnosis information are suitable for research beyond pure ECG analysis.	Limited public access requires specific agreements for use.	https://szpitalna.spzzlo.pl/pl/ekg

9. Studies in ECG biometrics

Many studies have been conducted in the field of identifying the human identity from the electrical fingerprint of the heart, and the following are the most important studies with promising results:

- **R. Boostani et al. (2018)**(Boostani et al., 2019)**:** In the proposed system, the electrocardiogram (ECG) data would undergo empirical mode decomposition (EMD) as a first step. Subsequently, the readings would extract instantaneous frequency, phase, amplitude, and entropy properties. The k-nearest neighbour method was ultimately employed to classify the attributes of individuals. EMD decomposed the raw ECG signals into their constituent sub-signals for ECG-based verification. Applying the Hilbert transform to the final empirical mode decomposition (EMD) component yielded the generation of the analytic representation of this low-frequency signal, comprising P and T waves. We successfully acquired several characteristics of this analytic signal, such as its instantaneous frequency, phase, amplitude, and entropy. Furthermore, several other strategies presently considered the epitome of competence were implemented. Analyzed at ten scales, the deconstructed ECG signals exhibited the highest mean verification rate. However, this approach required a high-dimensional feature space and involved substantial computational effort to calculate the distance between data points. This outcome was accomplished notwithstanding the considerable computational effort necessitated by the distance between the spots. Notwithstanding the existence of ten separate scales, this was the outcome. The augmented reality model, proposed as part of the recommended strategy, produced most minor new features. Due to their reliance on autocorrelation and covariance, statistical concepts are vulnerable to additional noise correlation-based approaches, and the AR model failed to achieve a high validation rate. Both strategies rely on autocorrelation and variance. Wavelet features, fiducial point and PCA, showed a high verification rate. However, it produced many features, resulting in a long recall phase and making it unsuitable for online use.
- **Zhang et al. (2019):** A scheme is presented that uses a deep convolutional neural network to process electrocardiogram (ECG) signals and extract distinct features for personality recognition. This method can extract unique features from an ECG clip without detecting any reference points, avoiding the time-consuming process of extracting fiducial feature points from the signal. In addition, feature maps' mean and standard deviation should be used as global classification features. A simplified voting mechanism is adopted to simplify the implementation of ECG-based human recognition in practical applications.
- **AlDuwaile & Saiful Islam (2021):** The proposed system uses deep learning methodologies to analyze the potential use of a short portion of the ECG signal for biometric identification purposes. The generalization skills of a small convolutional neural network (CNN) are enhanced when the entropy of a short segment of the heart signal is increased. This is done to facilitate the continuous expansion and improvement of the CNN. Furthermore, it studies how discrete, feature-dependent blind components of different durations can affect the overall performance of a recognition system. To evaluate their performance, experiments were conducted on two databases, one containing records of a single session and the other containing entries from multiple sessions. Furthermore, the effectiveness of the proposed

classifier is evaluated and compared with four established CNN models, namely GoogleNet, ResNet, MobileNet, and EfficientNet.

- **Hammad1 et al. (2021)** propose two comprehensive deep neural network models for authentication using ECG data. The prototype includes a convolutional neural network (CNN). On the other hand, the second model involves the development of a residual convolutional neural network (ResNet) with an attention mechanism known as ResNet-Attention, designed explicitly for human authentication. For validation purposes, ECG signals lasting 2 seconds were used. These signals were obtained from two distinct ECG databases: PTB and the Vital Signs Validation Initiative Here (CYBHi). The algorithm proposed by ResNet-Attention
- **Kwak (2022):** Inventing an electrocardiogram-based identifying method. The suggested method uses LSTM and CNN to generate a model. An electrocardiogram (ECG) signals a patient's heart rate using microcurrents. Patient biometric data is used for this purpose. This introduces noise into the measurements. Various devices remove noise during preprocessing. Segmenting the signals into cycles helps obtain R-peak information. The Long Short-Term Memory (LSTM) model analyzes ECG data for personal identification. FSST, WSST, STFT, and scalogram algorithms convert 1D ECG impulses to time frequency. After that, a 2D CNN is used to identify humans. Thus, preprocessing began with noise removal and baseline fluctuation adjustment. We compared a one-dimensional ECG signal with noise removed using one and two LSTM layers. Two highly accurate LSTM layers were used to complete the challenge. Thus, adding layers to the classification model may improve accuracy. However, this complicates the structure.
- **Hameed& Al-Tuwaijar. (2022)**: Introducing a biometric security system based on electrocardiography. The system relies on two distinct internal models. One model utilizes Convolutional Neural Networks (CNN) to facilitate deep learning. The other model employs three machine learning algorithms (Support Vector Machines, Bayes algorithm, and decision tree). These algorithms are accompanied by data processing operations that initialize the data and generate a new dataset of up to 2700 instances. This process involves creating fingerprints and adding 50 instances to the dataset. Each individual was assigned an extra fingerprint to enhance Reliability. The study's primary objective was to emphasize the significance of machine learning, as it employed three algorithms in contrast to the only method utilized in deep learning. Table 8 summarizes the studies above.

Table 8 - Summarized of previous studies.

RF	Year	Dataset	Methods	Limitation	Result
(Boostani et al., 2019)	2018	PTB (52 subjects FROM 290 Subjects)	EMD KNN PCA	EMD can be improved by adding time-varying characteristics to provide more independent and orthogonal components, reducing computing complexity. Since many clinical studies reveal age-related changes in ECG characteristics such as heart rate variability, more subjects must be studied. Age-related ECG alterations should also be considered.	**mAP** 95.14%
(Zhang et al., 2019)	2019	PTB (234 Subject) CEBSDB (20 Subject) NSRDB (18 Subject) MITDB (47 Subject)	NNC SVM	More than one data set with small groups was used, training was done on them, and only three out of four were reviewed, and few data were used in deep learning training. This	**Accuracy** PTB 99.54(SVM) 98.71(NNC) CEBSDB 99.85(NNC) 100(SVM) NSRDB

				contradicts the principle of deep learning and corresponds to machine learning only.	92.94(NNC) 95.28(SVM) MITDB No results reported
(Alduwaile & Islam, 2021)	2021	PTB (100 Subject) ECG-ID	CNN models: GoogLeNet, ResNet, MobileNet, and EfficientNet.	It is changing the frequency of the original dataset PTB from 1 to 0.5 to be compatible with the second dataset. The work was done separately for each dataset, AND Under these conditions, DO NOT investigate the performance of the brief segment's recognition. over a prolonged period of time, do not focus on creating a deeper learning machine that is resistant to changes in the signal.	**Accuracy** PTB GoogLeNet (99.76) ResNet 100 EfficientNet (99.70) MobileNet 100 Small CNN (99.83) ECG-ID GoogLeNet 90 Multi (93.87) ResNet (97.28) EfficientNet (83.10) MobileNet (87.51) Small CNN 94.18
(Hammad et al., 2021)	2021	• PTB • CYBHi	CNN ResNet	a few ECG records were analyzed, Sensitive to the ECG signal quality Proposed PTB and CYBHi)noted The number of subjects used from both data sets was not mentioned, but only 2,000 sample pulses were used from the two, and the results were separate for each group.)	PTB **Accuracy** (98.59) **Precision** 99.32 **Recall** (98.33) **F1score** (98.82) **CYBHi** **Accuracy** (99.72) **Precision** (100) **Recall** (99.50) **F1score** (99.79)
(Lee & Kwak, 2022)	2022	PTB (100 subjects)	CNN+LSTM	Converting the electrical signal to a one- or two-dimensional image means the system will work on the image containing the signal and the background, so the work needs a high execution time. The mechanism for dealing with the two algorithms has not been established, as the results were separated through the algorithm.	**Accuracy** LSTM 95.12% 2D-CNN 97.67%
(Hameed & Al-tuwaijari, 2022)	2022	PTB	CNN SVM DT NB	- The biometric system lacks a time parameter. In authentication systems, two conditions must be met: high accuracy in recognition and speed in recognition for it to be	**CNN** Accuracy= 99% Precision= 99.8% Recall= 99.7% F1-Score= 99.8% **SVM** Accuracy= 100% Precision= 100%

applied realistically. The researcher did not address the time and importance, and the evidence for that was the application of four algorithms sequentially, and the output is four results for accuracy; that is, one person has four results, and this is illogical -The proposed system does not use the (early stopping Epoch) method, which is considered the basis for stopping the training process without implementing more implementations, which causes wasting time. - Three machine learning algorithms were adopted, and only one algorithm is deep learning. This is an incorrect comparison if the research aims to compare algorithms, and this has not been clarified. - The processing process is a very good and effective way. Still, the application method was unsatisfactory because the original data amounted to 590 entries. Its size became 27000 entries, i.e., exaggeration in the number, and this large data will lead to a longitudinal training process. - The researcher used another data set, the largest updated version, with a size of approximately 22,000. If this method is adopted, the volume of data will be huge, which is illogical.	Recall= 100% F1-Score= 100% DT Accuracy= 96% Precision= 98% Recall= 98% F1-Score= 98% **NB** Accuracy= 92% Precision= 95% Recall= 96% F1-Score= 96%

10. **Conclusion**

Heart diseases and biometric systems are both dependent on the electrocardiogram because of their medical and security advantages at the same time. Because of this trend, many researchers have recently attracted many researchers and the abundance of research on it. In this scientific paper, the goal was to shed light on the most important basic concepts related to the electrocardiogram, as The topic of the unique features of the ECG was raised, which enables researchers to adopt them in biometric systems to identify people and also link them to the medical anatomy of the heart and the shape of the signal. The role of artificial intelligence, its divisions, and the methods most used by researchers in the ECG subject was highlighted in analytical tables, and the most important and famous ones were identified. Global data collection approved by researchers. Ultimately, the spotlight was on the studies researchers in biometric systems focused on for identifying people. The most important research of this sort will be recognized and studied in further detail as part of future research development efforts. Cardiology and biometric systems rely on ECGs because they provide medicinal and security benefits. Because of this trend, several academics and studies have lately been conducted on it.

The purpose of this scientific paper was to shed light on the most important basic concepts related to electrocardiography, as the topic of the unique features of electrocardiography was raised, allowing researchers to incorporate them into biometric systems to identify people while also linking them to the medical anatomy of the heart and the shape of the signal. The function of artificial intelligence, its divisions, and the approaches most commonly utilized by researchers in the field of ECG were emphasized using analytical tables, with the most essential and well-known ones recognized. Researchers authorize global data collecting. Finally, works on biometric methods for identifying individuals were highlighted. The future work to develop this research study can be stated in two dimensions. The first is about reviewing recently released research that shed light on smart systems based on gadgets such as smart watches and how to use them to extract data from them in order to build data sets at a cheaper cost for identifying people. The other axis is Making a comparison of the most recent research publications, sort of review and analysis

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