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THE ROLE OF ARTIFICIAL INTELLIGENCE IN DIAGNOSING HEART DISEASE IN HUMANS: A REVIEW

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ABSTRACT
The electrical activity of the heart and the electrocardiogram (ECG) signal are fundamentally related. In the study that has been published, the ECG signal has been examined and used for a number of applications. The monitoring of heart rate and the analysis of heart rhythm patterns, the detection and diagnosis of cardiac diseases, the identification of emotional states, and the use of biometric identification methods are a few examples of applications in the field. Several various phases may be involved in the analysis of electrocardiogram (ECG) data, depending on the type of study being done. Preprocessing, feature extraction, feature selection, feature modification, and classification are frequently included in these stages. Every stage must be finished in order for the analysis to go smoothly. Additionally, accurate success measures and the creation of an acceptable ECG signal database are prerequisites for the analysis of electrocardiogram (ECG) signals. Identification and diagnosis of various cardiac illnesses depend heavily on the ECG segmentation and feature extraction procedure. Electrocardiogram (ECG) signals are frequently obtained for a variety of purposes, including the diagnosis of cardiovascular conditions, the identification of arrhythmias, the provision of physiological feedback, the detection of sleep apnea, routine patient monitoring, the prediction of sudden cardiac arrest, and the creation of systems for identifying vital signs, emotional states, and physical activities. The ECG has been widely used for the diagnosis and prognosis of a variety of heart diseases. Currently, a range of cardiac diseases can be accurately identified by computerized automated reports, which can then generate an automated report. This academic paper aims to provide an overview of the most important problems associated with using deep learning and machine learning to diagnose diseases based on electrocardiography, as well as a review of research on these techniques and methods and a discussion of the major data sets used by researchers.
Keywords: *Electrocardiogram, Waves, Heartbeats, Diagnosing, Medical, Signals.*

1. Introduction

ECGs were originally documented in 1887 by Dutch scientist Willem Einthoven. The massive and complicated Einthoven machine takes several minutes to record a single ECG tracing. His work paved the way for contemporary ECG devices. Hospitals and clinics began using smaller, more portable ECG devices in the early 20th century. In the 1970s, digital ECG equipment made ECG data recording and analysis faster and more accurate (AL-Jibory et al., 2022; Al-Juboori, 2017; Shkara, 2018). Biomedical signals are predominantly gathered for the purpose of monitoring and identifying particular pathological or physiological conditions, with the aim of evaluating diagnosis and treatment. In certain instances, they are employed in fundamental scientific investigations to decipher specific biological mechanisms and ultimately replicate them through simulation. In addition, contemporary technology enables the recording of these signals across several channels (Sandau et al., 2017; Rahma & Salman, 2022). The novel aspects of signal processing difficulties emerge when attempting to measure crucial physiological connections across diverse channels. In each of these scenarios, the conventional objectives of signal processing encompass tasks such as diminishing noise, accurately assessing the signal model along with its elements using analysis (employed for purposes like system identification in modeling and control), distilling features to ascertain functionality, and foreseeing potential abnormal or functional occurrences, as observed in applications like cardiac assist devices (Porle et al., 2015; Abed et al., 2023). For a variety of reasons, signal-processing techniques are extensively used in biological applications (Smith et al., 2019). The biological signal that is being measured is typically thought of as an additive combination of signal and noise. The selection of an appropriate signal-processing technique is crucial due to the potential sources of noise, which may arise from many components such as sensors, amplifiers, filters, and so on. Additionally, noise can also originate from electromagnetic interference (EMI) or any signal that lacks synchronization and correlation with the noise characteristics in a broader context (Cluitmans et al., 2018, Sadiq & Mahmood, 2014). Diagnoses can be aided by automated ECG analyzers. They won't take the position of medical experts, but their decision might be seen as an unbiased second opinion. The currently existing automated diagnosis methods have a number of drawbacks and shortcomings, including a lack of accuracy in recognizing ischemia events, fibrillations, and arrhythmia identification (Choi et al., 2010). In recent years, computer-assisted ECG interpretation has substantially helped automatic cardiac condition identification. CVD has a much greater fatality rate when compared to other joint diseases like cancer. Therefore, it makes sense to need automated ways to evaluate and find it. Since the introduction of mobile computing devices like tablets and smartphones, many scholars have worked on creating algorithms for CVD detection (Satija et al., 2018). Wearable diagnostic methods for identifying and evaluating cardiovascular disease (CVD) are now more acceptable thanks to these portable computer devices. There is a rising need to create new systems that try to address these issues in light of the current COVID-19 epidemic, which has put a burden on hospital capacity and medical staff due to internet traffic. One strategy involves choosing only the most important leads and lowering the required bandwidth size in order to reduce the quantity of leads needed to transmit the electrocardiogram (ECG) signal. The need to reduce the bandwidth utilized to transmit the electrocardiogram (ECG) signal is what spurs the development of new technologies (Abdeldayem & Bourlai, 2020). There is still a need to find a reasonable and cost-effective solution to the complex problems. Healthcare facilities in countries that have been severely hit by the pandemic are on the verge of collapse as a result of ongoing issues with departmental and hospital capacity. Modern devices' main goal is to acquire as much information as possible regarding the electrical activity of the heart while using the fewest possible lines. There is a greater emphasis on technological alternatives in the present difficult circumstances, and there is increased pressure to change healthcare practices from traditional techniques to technology-driven solutions (Abdeldayem & Bourlai, 2020). Many healthcare technologies, including machine learning, cloud computing, edge computing, and deep learning, have made major advancements over time, including the Internet of Things (IoT). It is important to stress that these advancements were not specifically created to withstand the intense pressure applied during unexpected events like pandemics (Zokaee & Faez, 2012). Healthcare technology must drastically change in order to solve the deteriorating situation of the global healthcare infrastructure. Situations involving remote health monitoring (RM) frequently entail wireless signal transmission to advanced healthcare facilities nearby. These situations often include bandwidth, storage, and data transmission time as their primary constraints. Physical scientists and engineers strive to overcome these challenges, find novel solutions, and pinpoint new problems. Internet telemedicine systems can offer speedy and effective medical care, which is one of their many advantages. Online healthcare solutions frequently rely on sophisticated and cutting-edge wireless sensor and wearable technologies. Rapid technological improvements have led to a large expansion in the range of remote health monitoring systems (Hong et al., 2020).

In summarized AI and Modern Computational ECG Analysis in recent years, AI and computational methods have revolutionized ECG analysis and diagnosis. Artificial intelligence can recognize and classify ECG features like P waves, QRS complexes, and T waves. This can improve clinicians' heart diagnosis accuracy and efficiency.AI can also generate ECG-based heart disease biomarkers for early detection. For instance, AI algorithms can detect small ECG abnormalities that predict heart attack or stroke risk. (Al-Tamimi & Sulong, 2014; Ghadi & Salman, 2022).

This essay examines the prevalent topic in electrocardiography (ECG) from the perspective of artificial intelligence-based technology.

2. Tested Type

Numerous different sorts of tests may be used to make the diagnosis of heart illness. Blood tests and chest X-rays aren't the only ones that can be used to detect cardiac disease. The following tests can also be utilized:

- **ECG or EKG (Jembula et al., 2013):** The recording and examination of electrical impulses emanating from the heart are done using the non-invasive, painless electrocardiogram (ECG). The heartbeat can determine if it is beating too swiftly or too slowly, as show in Fig. 1.

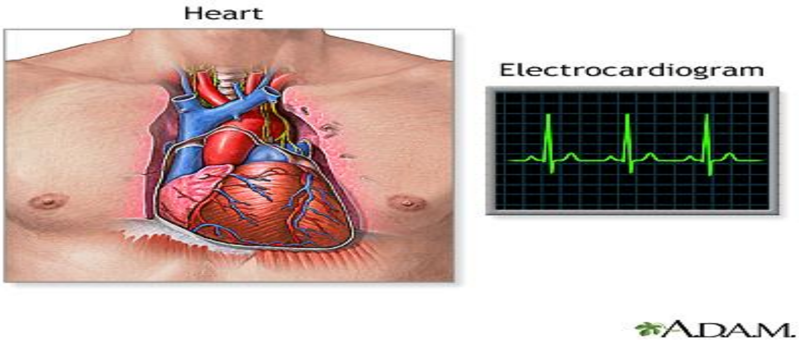

Fig. 1. ECG

- **Holter monitoring (Todorov et al., 2019):** a portable ECG that a person wears for at least a day to track their heartbeat as they go about their everyday activities. This test has the capacity to find irregular heartbeats that are undetectable by a conventional ECG. As show in Fig. 2.

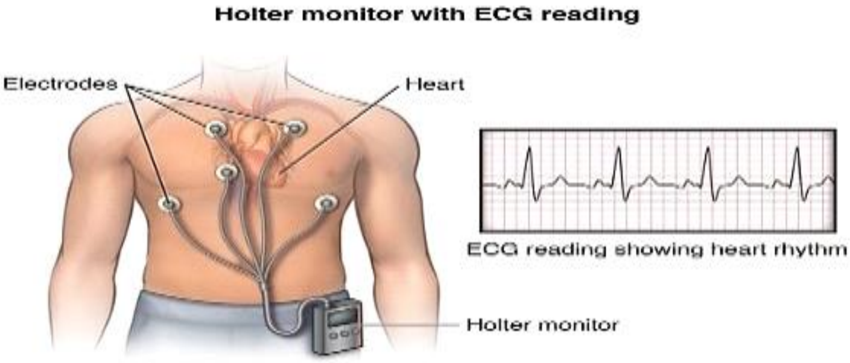

Fig. 2. Holter Monitoring.

- **Echocardiogram (Palermi et al., 2021:** In this non-invasive test, sound waves are used to create images of the heart in motion. It demonstrates the movement of blood through the heart's valves. An echocardiography can determine whether a valve is leaking or has been constricted. As show in Fig. 3.

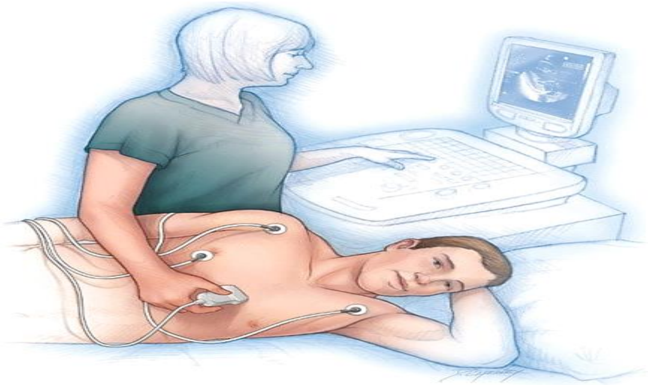

Fig. 3. Echocardiogram.

- **Exercise or stress (Krishnan & Athavale, 2018):** During testing, it is customary to use a stationary bike or a treadmill while keeping an eye on your heart rate. Exercise testing can help determine how the heart reacts to different levels of physical activity as well as whether heart disease symptoms appear during exercise. Medications may be prescribed if physical activity is not an option, as show in Fig. 4.

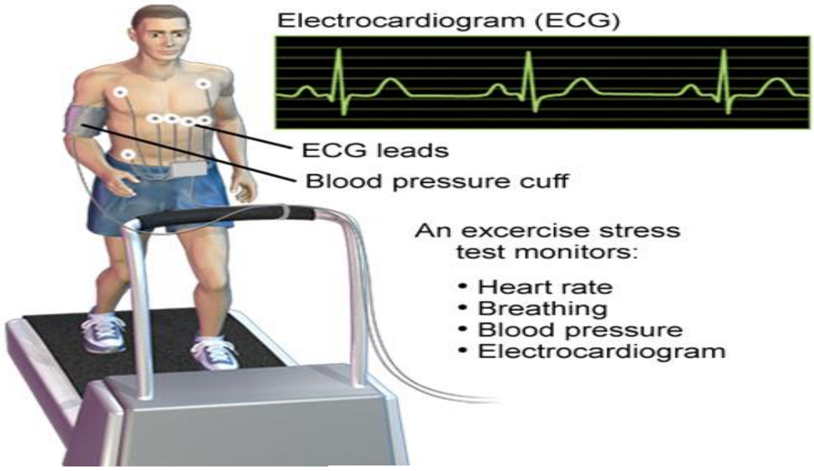

Fig. 4. Exercise

- **Cardiac catheterization (Yannopoulos et al., 2019):** A heart artery occlusion may be discovered by this examination. A long, thin, flexible tube (catheter) is inserted into a blood artery, commonly in the wrist or groin, in order to reach the heart. The dye is supplied to the heart's arteries through the catheter. The dye used during the examination enhances the arteries' visibility on X-rays, as show in Fig. 5.

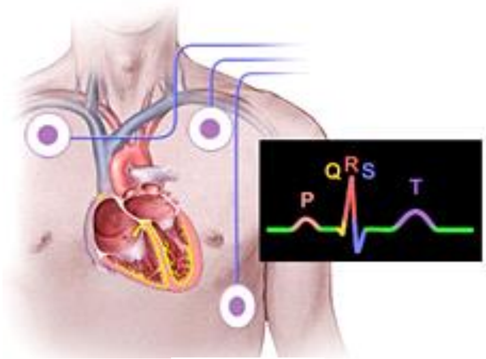

Fig. 5. Stress

- **Heart (cardiac) CT scan (Yannopoulos et al., 2019):** During a heart CT scan, you will recline on a table inside a doughnut-shaped scanner. Your body is rotated around by the machine's internal spinning X-ray tube as it takes pictures of your chest and heart from various perspectives. as show in Fig. 6 and 7.

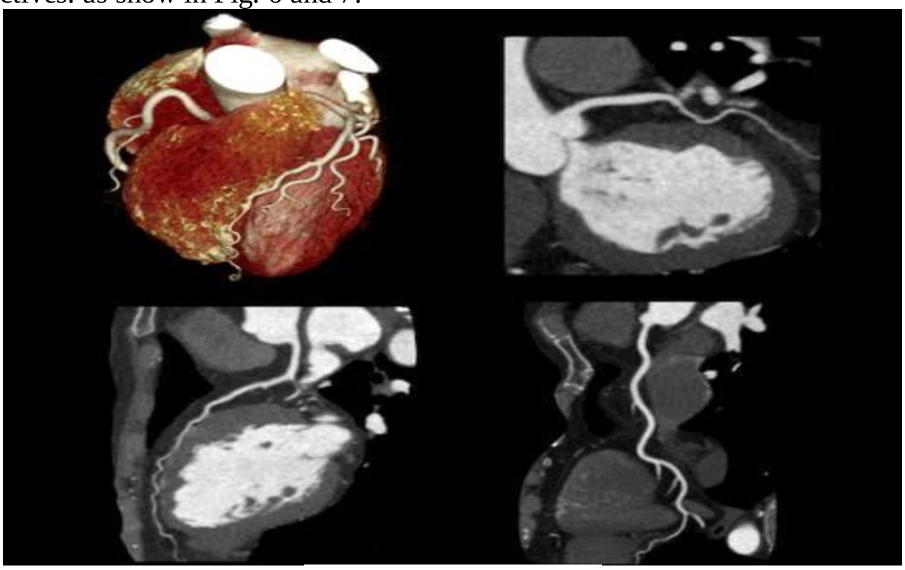

Fig. 6. Heart (cardiac) CT scan

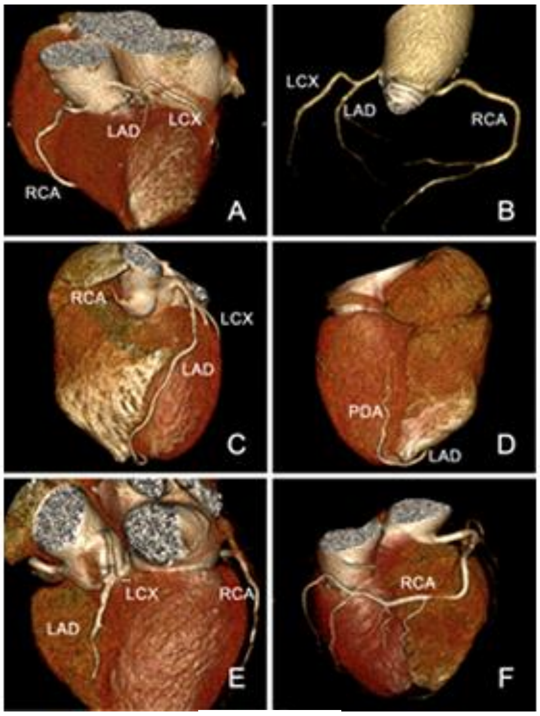

Fig. 7. Cardiac

- **Heart (cardiac) magnetic resonance imaging (MRI) scan (Pirruccello et al., 2020):** Using a magnetic field and radio waves produced by a computer, it is possible to obtain detailed photographs of the heart. The subsequent (Fig. 8) presents a summary of the several tests used to identify cardiac disease.

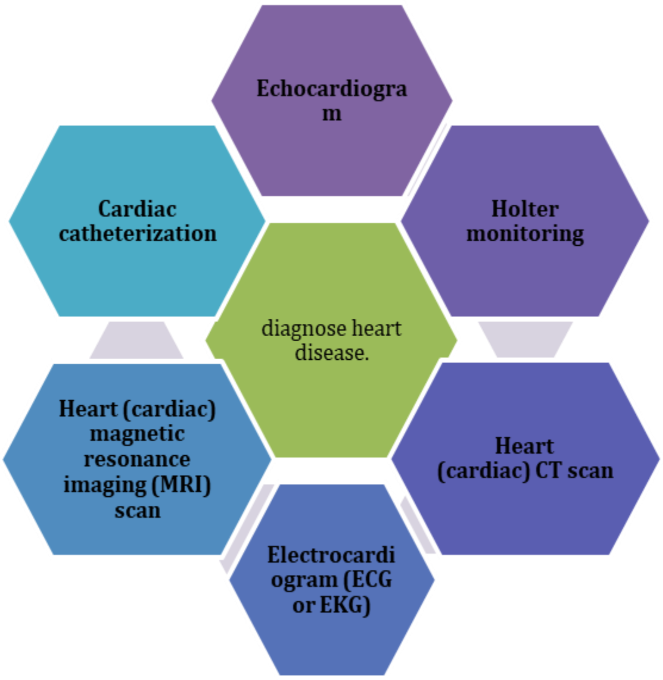

Fig. 8. Testing To Diagnose Heart Disease

Which diagnostic procedures are most effective for identifying heart disease depends on the symptoms and risk factors of each patient. The chance of more serious issues, including a heart attack or stroke, can be decreased by receiving a diagnosis of heart disease as soon as possible (Methods and Studies for Human Electrocardiogram: A Survey, n.d.).

- **Heart Anatomy and Physiology**

Transporting nutrients and oxygen throughout the body is the main duty of the cardiovascular system. The Heart is likened to two parallel pumps that operate in sequence to push fluid through a network of channels before returning to the pumps (Hassan et al., 2016). While the other pump circulates blood throughout the body, the first one carries blood to the lungs so that it can take oxygen. The cycle then starts over when the blood returns to the Heart. An atrium and a ventricle are the two chambers that make up each pump in an anatomical model of the heart. The atria have a very small impact on blood flow because of their small size. The main job of the ventricles is to transfer blood from the circulatory system to the ventricle. The heart's ventricles make up the majority of its volume, with the left ventricle being larger than the right. They draw blood from the atria and deliver it to the rest of the body through the arteries (Arooj et al., 2022). Figure (9) the four heart chambers' anatomical configuration is depicted in the figure. Within the cardiac structure, the ventricles are positioned inferiorly while the atria are positioned superiorly (Al Jibory et al., 2022). The Heart's blood flow is controlled by a valve system. The flexible tissue that makes up the heart valves is arranged in such a way that only one direction of blood flow is possible. Table (1) summarizes the anatomy and physiology of the Heart.

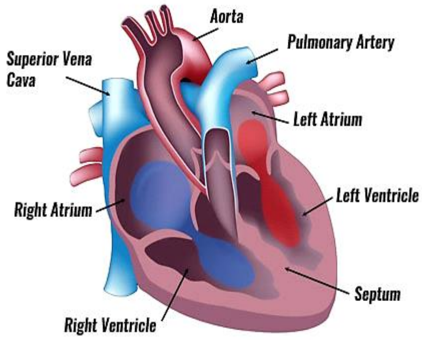

Fig. 9. Anatomy of the Heart (Anterior View) (Hassan et al., 2016).

Table 1- Anatomy And Physiology of The Heart (Dahou Et Al., 2019).

Anatomy	Physiology
Chambers	The four chambers of the human heart are divided into two atria and two ventricles. The ventricles act as the pumps that send blood into the systemic circulation, while the atria serve as the organs that receive blood from the systemic circulation.
Valves	The valves between the chambers effectively stop blood from flowing backward. The pulmonary valve and aortic valve are located at the intersections of the ventricles and the main arteries that feed blood to the pulmonary and systemic circulations, respectively. The mitral valve and tricuspid valve are located in the intertribal and interventricular septa, respectively.
Walls	The epicardium, the myocardium, and the endocardium are the three layers that make up the heart's wall. The endocardium, the myocardium, and the epicardium are the three layers nearest to the surface, middle, and center of the heart, respectively.
Blood supply	The coronary arteries are in charge of supplying the heart muscle with blood. The main artery that carries blood away from the heart is the aorta. The aorta has branches that branch out into the coronary arteries.
Electrical system	The electrical system of the heart is in charge of controlling the heartbeat's rhythm. The electrical impulses that start the heart's beating are created by the sinoatrial node, which is situated in the right atrium. Electrical impulses that pass through the heart and enter each heart chamber cause the heart's chambers to contract.

- **Disease and Factors of Heart**

More disorders can impact the Heart's functionality, and the sooner they are found the better for human health (Liu et al., 2018; Abd-Alzhra & Al-Tamimi, 2022). The following table lists a few of the ailments and contributing elements that earlier academics identified using artificial intelligence. Table (2) below lists the heart's diseases and contributing factors.

Table 2 - Disease and Factors of Heart

Disease	
Coronary artery disease (CAD) (Okrainec et al., 2004)	The most typical form of heart disease is this one. When the coronary arteries, which carry blood to the heart, constrict or are

	clogged, it happens. Angina, a heart attack, or sudden cardiac death can result from this.
Heart failure (Groenewegen et al., 2020)	Heart failure, sometimes referred to as cardiac insufficiency, is a medical condition when the heart is unable to efficiently circulate blood to meet the body's physiological needs. It can be brought on by a number of conditions, including coronary artery disease (CAD), high blood pressure, and others.
Arrhythmia (Moody & Mark, 2001)	This heartbeat is unsteady. Arrhythmias can be mild or dangerous, causing heart failure or unexpected cardiac death.
Cardiomyopathy (Ahola & Langer, 2023)	The cardiac muscle is afflicted by this illness. It may be brought on by genetic causes, high blood pressure, or alcohol misuse.
Congenital heart defects (Buteau et al., 2023)	These are birth-related cardiac conditions. They might be modest to really severe.
Factors (Bakar et al., 2023)	
Age	As you become older, your risk of acquiring heart disease increases.
Family history	People who have a family history of heart disease are more likely to develop the ailment.
Race	Compared to Caucasians, people of color, Hispanics, and Native Americans have a higher chance of developing heart disease.
Gender	Compared to women, men are more prone to acquire heart disease.
High blood pressure	Heart disease is significantly increased by high blood pressure.
High cholesterol	Heart disease risk can also be increased by high cholesterol.
Diabetes	A significant extra risk factor for developing heart disease is diabetes.
Smoking	Smoking itself poses a significant danger for the emergence of heart disease.
Obesity	Heart disease is also significantly impacted by obesity.

- **Background of Electrocardiogram ECG**

The first evidence that the heart had electric currents was discovered more than 150 years ago. Due to his work on the ECG, Dutch scientist Willem Einthoven was awarded the Nobel Prize in Physiology or Medicine in 1924. This achievement took place at the start of the 20th century. From a medical and security perspective, electrocardiograms (ECGs) can be utilized to look for and analyze cardiac problems. The electrical activity of the heart is measured by the ECG by comparing differences in electrical potential between two locations. Explains the benefits of the ECG and its physiological foundation (Dong et al., 2018). Figure (10) shows the (ECG) of a healthy individual.

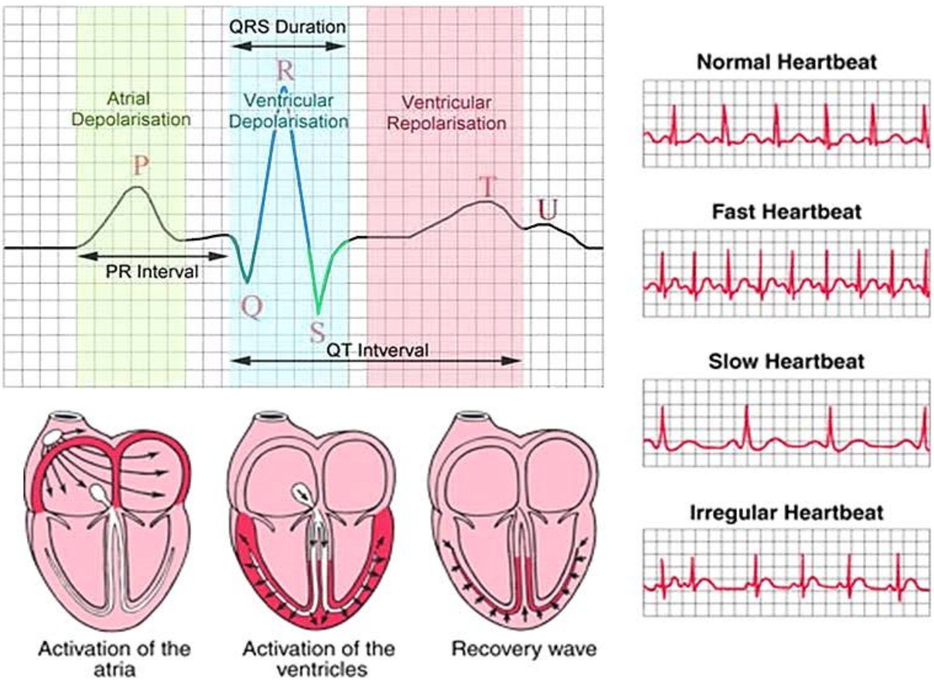

Fig. 10. (ECG) of a healthy and unhealthy individual.

The key characteristics of the cardiogram can be distilled in Table (3) based on the preceding Figure.

Table 3 - Features of ECG.

Features	Description
P	Atrial depolarization is indicated by the ECG's initial positive deflection.
Q	An early inversion of the positive component of the QRS complex.
R	An electrocardiogram (ECG) is a vital tool for observing the QRS complex, which is distinguished by the P wave's initial upward deflection. Positive initial deflection is a phenomena that is seen.
S	The wave corresponds to the final depolarization of the ventricles near the center of the heart.
T	The repolarization of the ventricles is represented by this wave.
Q	Depolarization of the heart's ventricles. In the QRS complex, the right and left ventricles depolarize quickly. Atria lack the muscle that ventricles do. Thus, the amplitude of the QRS complex typically surpasses that of the P wave.

6. Artificial Intelligence in the Detection Disease of Heart

The use of AI in the early diagnosis of heart illness is promising. A system that uses artificial intelligence to diagnose diseases has become urgently necessary due to the advancement of technology in the modern era (Ciccarelli et al., 2023; Al-Tamimi & AL-Khafaji, 2022). The role of artificial intelligence in the detection of heart diseases is depicted in Table (4).

Table 4 - Artificial Intelligence in the Detection Disease of Heart (Ueda et al., 2023) (Ciccarelli et al., 2023).

AI heart disease detection benefits		
1	Increased accuracy	When it comes to diagnosing heart problems, AI may be more accurate than traditional techniques like ECG analysis.
2	Early detection	With earlier therapy and better results, AI can help in the early diagnosis of cardiac illness.
3	Remote monitoring	Artificial intelligence can monitor patients remotely, enabling early detection of cardiac problems and a reduction in the requirement for in-person consultations.
AI heart disease detection challenges		
1	Data availability	Large datasets of labeled data are needed to train AI algorithms. It can be difficult to find this information, especially for rare cardiac disorders.
2	Interpretability	It can be tricky to understand why a particular forecast was made since AI algorithms might be difficult to interpret.
3	Bias	Because AI algorithms are prone to bias, they may make incorrect predictions.

6.1 Methods in Artificial Intelligence

Artificial intelligence (AI) is now used in a number of ways to help with heart disease diagnosis, treatment, and prevention. We currently use a range of tactics, some of which are listed below (Methods and Studies for Human Electrocardiogram: A Survey, n.d.) (Kim & Kim, 2017):

- **Machine learning:** To find patterns linked to cardiac disease, big medical data datasets can be analyzed using machine learning techniques. The creation of fresh diagnostic techniques and therapeutic plans can then be made using this information.
- **Deep learning:** Three or more layers of neural networks are used in deep learning, which is a type of machine learning. These neural networks mimic the human brain to "learn" from enormous amounts of data. A neural network with a single layer may only be able to forecast the future roughly, but by incorporating hidden layers, one can improve and boost prediction accuracy. A significant number of AI apps and services that automate analytical and physical operations without the need for human input are also powered by deep learning. Deep learning has applications in the powering of digital assistants, voice-activated TV remotes, credit card fraud detection, and self-driving cars.
- **Natural language processing:** To identify people at risk for heart disease, natural language processing (NLP) can examine medical records and other text-based data. Then, using this knowledge, preventive measures can be targeted at the people who will benefit from them the most.

- **Computer vision:** To evaluate medical images like ECGs and echocardiograms and find indications of heart disease. Heart disease can be identified earlier and with more precision using the information provided.
- **Robotics:** Robotics can be utilized to create new medical gadgets for the detection and treatment of cardiac disease. Robots, for instance, can carry out minimally invasive cardiac surgery.

The distinction of ML and DL techniques is depicted in Figure (11).
The following point describes the Figure 11:

- **Machine learning Techniques**
- **Support Vector Machine (SVM) (Ibrahim et al., 2022):** is a machine learning technique that divides data points into distinct groups while enhancing how much they diverge from one another. It is widely used in a variety of fields, including sentiment analysis, bioinformatics, image categorization, and text categorization. Support vector machines (SVMs), which can handle both linear and nonlinear data, have shown to be useful in classification applications. By selecting the appropriate decision boundary using patterns discovered from training data, it correctly categorizes unknown data. SVM is a useful tool in many disciplines thanks to its adaptability.
- **Random Forest (RF) (Khajavi & Rastgoo, 2023):** a machine learning approach that makes predictions for classification and regression tasks using decision trees. It seeks to improve accuracy by tackling over fitting and successfully managing datasets with huge dimensions, increasing machine learning's overall efficacy.
- **Hidden Markov Models (HMM) (Glennie et al., 2023):** are mathematical representations of temporal variations and transitions between emotional states. They represent observed data points as unidentified states linked to particular emotions, enabling analysis of physiological, verbal, and facial expression cues to uncover concealed emotional states. HMMs are useful tools for comprehending how emotions are dynamic and for capturing changes in emotional states. They are useful for analyzing sequential data and inferring emotional changes in certain situations or conversations. In order to improve the accuracy and comprehension of emotional dynamics, researchers are using HMMs, which could have an impact on areas including affective computing, human-computer interaction, and psychological research.
- **K-Nearest Neighbor (KNN) (Webb et al., 2010):** is a straightforward but effective approach of classification that groups samples in the feature space according on their closeness to other neighboring samples. It acknowledges that things with related characteristics frequently belong to the same category. The algorithm determines the class of a test sample based on its k nearest neighbors using a user-defined parameter called k. Due to its simplicity and efficiency, KNN is adaptable and frequently used in a variety of domains, including pattern recognition, text categorization, suggestion systems, and image identification.
- **Naïve Bayes (Bassiouni et al., 2018):** is a Bayesian probabilistic classifier that divides cases into predetermined groups by estimating the likelihood of each group given input data. Text categorization, spam filtering, sentiment analysis, recommendation systems, and medical diagnosis are just a few of the areas where it is extensively employed. Tasks involving natural language processing, where discrete or categorical features are frequently used, benefit greatly from the use of naive Bayes. It may be used to analyze email content, identify the polarity of customer evaluations, and classify documents according to various subjects. When data demonstrate conditional independence and the classifier needs to be trained and deployed fast, its simplicity and efficiency make it a popular option.

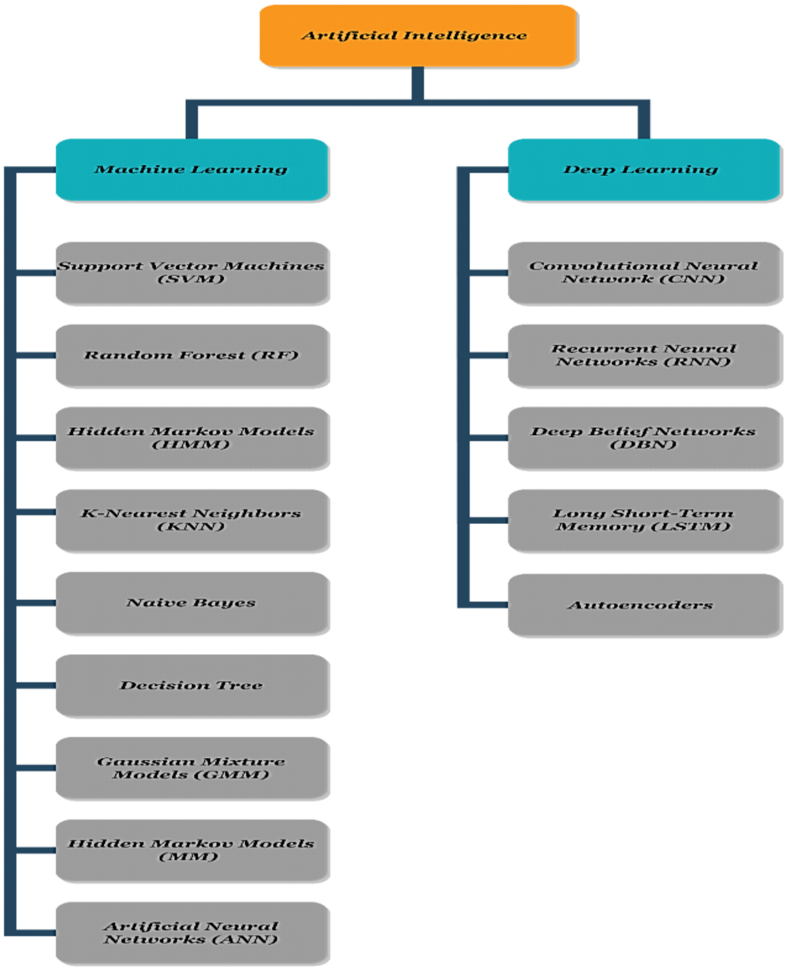

Fig.11. Emotion Recognition Using ML and DL Technologies.

- **Decision Tree (Myles et al., 2004):** a machine learning technique that builds a model that resembles a tree to make judgments or predictions using labeled data. It has been successful in the fields of marketing, finance, healthcare, and customer relationship management and is frequently used in classification and regression assignments. Decision Tree models can analyze financial data, categorize diseases, forecast customer behavior, and help businesses make wise decisions. It is a useful tool in data analysis and decision-making processes across a variety of areas due to its adaptability and interpretability.
- **Gaussian Mixture Model (GMM) (Sekaran et al., 2020):** allows for applications in pattern recognition, data clustering, and density estimation by representing the probability distribution of a dataset as a combination of several Gaussian distributions. By dividing data points based on probability density and estimating density functions, they are able to capture the diversity and peculiarities of speech patterns.

  Artificial Neural Network (ANN) (Jambukia et al., 2015): With the aim of automating cognitive activities including pattern recognition, categorization, regression, and decision-making, develop computational models based on the anatomy of the human brain. They learn from the data that is put into them and adjust their parameters as a result of training, allowing them to produce precise predictions and solutions across a range of industries.
- **Deep Learning Techniques**
- **Convolutional Neural Network (CNN) (Hammad et al., 2019):** Use deep learning techniques to process visual data, analyze and recognize images, and extract useful features. They have revolutionized image analysis jobs and advanced our comprehension of visual information in a variety of sectors. They are employed in a variety of domains such computer vision, autonomous driving, medical imaging, surveillance, and natural language processing.
- **Recurrent Neural Networks (RNN) (Lynn et al., 2019):** are used in sequence modeling and analysis to capture temporal dependencies and sequential information in data using artificial

neural networks. They excel at recognizing handwriting, voice, and natural language, capturing context and relationships between words or characters. In time series analysis, RNNs are also used for accurate forecasting, anomaly detection, and weather forecasting. For applications requiring sequential data processing and modeling across various fields, RNNs offer solutions.

- **Deep Belief Networks (DBN) (Alqahtani et al., 2023):** are deep learning models that can recognize complicated patterns and dependencies in high-dimensional data by learning hierarchical representations of the data. They are utilized in many different fields, including as bioinformatics, natural language processing, computer vision, and speech recognition. While RNNs are better at sequential data analysis, time series analysis, and handwriting recognition, DBNs are utilized for picture categorization, object identification, and image synthesis. For problems requiring sequential data processing and modeling, both areas offer solutions.
- **Long Short–Term Memory (LSTM) (Ganguly et al., 2020):** an architecture for recurrent neural networks that is intended to deal with sequential data with long-term dependencies. It effectively models and predicts sequences thanks to its ability to capture and hold onto crucial information across long time periods. Natural language processing applications like translation, sentiment analysis, speech recognition, and time series forecasting activities like stock market and weather forecasting are all very well suited for LSTM. Additionally, by taking into account the temporal connections between frames or regions, it excels at picture and video analysis, enhancing comprehension and interpretation of visual sequences.
- **The dataset used in heart Disease**
  Five enormous datasets, the majority of which were acquired from medical equipment, are used to evaluate ECG studies. Some of them were caused by medical equipment. The data on medical devices is more informative since it contains more leads than the data on healthcare equipment. Data on medical equipment is more challenging to come by. For continuous ECG monitoring, smart bracelets and other devices are becoming more and more popular. An electrocardiogram with 12 or 15 leads can identify more anomalies than one with just one lead (Maršánová et al., 2021). Explanation of the most common datasets in Table (5).

Table 5 - The Most Critical Global Data Sets Used by Researchers

RE	Data Name	Data description
(Moody & Mark, 2001)	MIT-BIH Arrhythmia Database	48 half-hour ECG recordings from 47 different patients at Boston's Beth Israel Hospital (now known as the Beth Israel Deaconess Medical Center) were collected. Every single ECG data series has a sampling frequency of 360 hertz, a resolution of 11 bits, and a range of 10 mV. Comprehensive diagnoses of the beat and rhythm may be found in this dataset.
(Nguyen et al., 2021)	PhysioNet Computing in Cardiology Challenge 2017 dataset	Comprises 8,528 ECGs from 9 to 60 seconds that were recorded by an AliveCor medical equipment. 7, 17 AF recordings, 2,557 other recordings, and 5,150 regular recordings. 46 recordings of noise. Test recordings from 3658 students are kept private for scoring. It was gathered. Medical equipment.
(Physionet, 2019)	Diagnostic ECG Database of the PTB	549 15-channel ECG data were supplied by 290 people. Sampling at 10 kHz is feasible. One of the eight heart disorders affects 216 people, whereas 52 people are healthy and 22 people are unclear.
(S. & Ramaraj, 2021)	PTB XL	It contains 21837 clinical 12-lead ECGs from 18885 patients that were recorded over a 10-second interval. The waveform record was given different ECG statements by as many as two cardiologists. The diagnostic, form, and rhythm ECG statements are among the seventy-one that adhere to the SCP-ECG. Please provide recommended dataset splits so that machine learning strategies can be contrasted. The dataset's thorough annotation makes it suitable for creating and using automatic ECG interpretation algorithms. The dataset contains extensive metadata on demographics, infarction characteristics,

		diagnostic ECG statement likelihoods, and signal parameters.
(Lastre-Dominguez et al., 2019)	Atrial Fibrillation Database at MIT-BIH	Consists of 25 recordings of patients with paroxysmal atrial fibrillation at 250 Hz on a two-lead ECG lasting 10 hours each. An ambulance at Boston's Beth Israel Hospital used the PhysioNet Computing in Cardiology Challenge 2017 dataset to test deep learning techniques. In the hidden test set, only strategies with scores greater than 0.8 are allowed.
(Liu et al., 2018)	CPSC-2018 China Physiological Signal Challenge	The first China Physiological Signal Challenge will take place in Nanjing, China, at the 7th International Conference on Biomedical Engineering and Biotechnology (ICBEB 2018). The entire conference will feature this tournament. By offering a platform for open-source data and physiological signal processing methods, the CSPC hopes to promote open-source research patterns for cardiovascular disease detection and prediction in China. By offering a platform for open-source data and algorithms, this will be accomplished. Additionally, it aims to promote the creation of algorithms that can recognize irregular rhythms or morphologies in 12-lead ECGs lasting a few to tens of seconds. These irregularities may last for a short while or for a long time. In addition to the conventional kind, the 12-lead ECGs used in CPSC 2018 included eight aberrant varieties.
(Vasconcellos et al., 2023)	Dataset for categorizing heartbeats on ECGs	The dataset consists of two sets of heartbeat signals obtained from well-known datasets in the field of heartbeat classification, the MIT-BIH Arrhythmia Dataset and The PTB Diagnostic ECG Database. Both of these collections offer a sufficient number of instances for convolutional neural network training. Additionally, this dataset has been used to observe some of the capabilities of transfer learning on it as well as to investigate the classification of heartbeats using deep neural network architectures. The readings on an electrocardiogram (ECG) correspond to the shapes of the heartbeats. This claim is true both in the normal situation and when it is affected by different arrhythmias and myocardial infarctions. The signals are first processed before being divided into segments, where each segment represents a distinct heartbeat.

- **Previous studies in the field of diagnosing heart disease**

There are many studies on the topic of ECG, and the following are some studies that were close in terms of the idea of the proposed system and were summarized in the following section:

In (**Hao Dai *et al.*, 2021**): The Physiobank PTB-ECG database is used in this study. Firstly, ECG signals are segmented into different intervals (one-second, two-seconds and three-seconds), without any wave detection, and three datasets are obtained. Secondly, as an alternative to any complex preprocessing, durations of raw ECG signals have been considered as input with simple min-max normalization. Lastly, a ten-fold cross- validation method is employed for one-second ECG signals and also tested on other two datasets (two- seconds and three-seconds). The proposed CNN acquires the highest performance, having an accuracy, sensitivity, and specificity of 99.59%, 99.04%, and 99.87%, respectively, with one- second ECG signals. The overall accuracy, sensitivity, and specificity obtained are 99.80%, 99.48%, and 99.93%, respectively, using two-seconds of signals with pre-trained proposed models. The accuracy, sensitivity, and specificity of segmented ECG tested by three-seconds signals are 99.84%, 99.52%, and 99.95%, respectively.

In (**Mahwish Naz *et al.*, 2021**): An ECG is the major analytical tool used to interpret and record ECG signals. ECG signals are nonlinear and difficult to interpret and analyze. We propose a new deep learning approach for the detection of VA. Initially, the ECG signals are transformed into images that have not been done before. Later, these images are normalized and utilized to train the AlexNet, VGG-16 and Inception-v3 deep learning models. Transfer learning is performed to train a model and extract the deep features from different output layers. After that, the features are fused by a concatenation approach, and the best features are selected using a heuristic entropy calculation approach. Finally, supervised learning classifiers are utilized for final feature classification. The results are evaluated on the MIT-BIH dataset and achieved an accuracy of 97.6% (using Cubic Support Vector Machine as a final stage classifier).

In (**Adyasha Rath *et al.*, 2021**): In this paper and the required classification models have been developed and tested. The Generative Adversarial Network (GAN) model is chosen with an objective to deal with imbalanced data by generating and using additional fake data for detection purpose. Further, an ensemble model using long short-term memory (LSTM) and GAN is developed in this paper which demonstrates higher performance compared to individual DL model used in this paper. The simulation results using standard MIT-BIH show that the proposed GAN-LSTM model provides the highest accuracy, F1-score and area under curve (AUC) of 0.992, 0.987 and 0.984 respectively compared to other models. Similarly, for PTB-ECG dataset the GAN-LSTM model outperforms all other models with accuracy, F1-score and AUC of 0.994, 0.993 and 0.995 respectively. It is observed that out of the five models investigated, the GAN model performs the best whereas the detection potentiality of the NB model is the lowest. Further research work can be carried out by choosing all other different ensemble models and using other different datasets and the performance can be similarly obtained and compared. The proposed best detection methodology can also be applied to other diseases and healthcare problems.

In (**Khiem H. Le *et al.*, 2023**): In this research developed a novel deep learning system to accurately identify multiple cardiovascular abnormalities by using only three ECG leads. Specifically, use three separate one dimensional CNN (1D-CNNs) as backbones to extract features from three input ECG leads separately. The architecture of 1D-CNNs is redesigned for high performance and low computational cost. A novel Lead-wise Attention module is then introduced to aggregate outputs from these three backbones, resulting in a more robust representation which is then passed through a Fully Connected (FC) layer to perform classification. Moreover, to make the system's prediction clinically explainable, the Grad-CAM technique is modified to produce a high meaningful lead-wise explanation. Finally, we employ a pruning technique to reduce system size, forcing it suitable for deployment on hardware-constrained platforms. The proposed lightweight, explainable system is named LightX3ECG. Proposed method got classification performance in terms of F1 scores of 0.9718 and 0.8004 on two large-scale ECG datasets, i.e., Chapman and CPSC-2018, respectively, which surpassed current state-of-the-art methods while achieving higher computational and storage efficiency. Visual examinations and a sanity check were also performed to demonstrate the strength of our system's interpretability.

In (**Mou Wang *et al.*, 2023**): Atrial fibrillation (AF) is the most common type of sustained cardiac arrhythmia, and is associated with stroke, coronary artery disease and mortality. In this paper, we propose an end-to-end AF recognition method with dual-path recurrent neural network (DPRNN) from single-lead ECG. The model takes the whole ECG as input, and DPRNN splits the ECG into shorter segments and models the sequence between intra- and inter-segment iteratively. A mix-up operation is used for data augmentation, which overcomes the issue of limited data. The proposed method evaluated on the dataset from PhysioNet Challenge 2017. Experimental results are Accuracy 0.971 and F1 score 0.953.

In (**Enock Khondowe *et al.*, 2023**): In this work present a One-Dimensional Convolutional Neural Network (1D-CNN) method for classifying electrocardiograms. The model consists of three 1D-CNN layers, followed by a fully connected layer and a SoftMax layer for classification. The aforementioned approach was trained and tested using the widely used MIT-BIH arrhythmia dataset and the PTB Diagnostic Databases, which are open-source and freely accessible to the public. The study shows that 1D-CNNs outperform other methods, achieving exceptional performance with high generalization ability, leading to a state-of-the-art average classification accuracy of 99.0%. The proposed model is efficient in learning features with imbalanced samples and enhances model convergence, resulting in improved accuracy. the following table 6 summarized the **Previous studies.**

Table 6 - Summarized Of Previous Studies

Year	Another's	Title	Data Set	Methods	Results
2021	Hao Dai, Hsin-Ginn Hwang, Vincent S. Tseng	Convolutional Neural Network Based Automatic Screening Tool for	PTB-ECG	CNN	Set A (1s) Accuracy: 99.59% Sensitivity:99.04% Specificity:99.87%

		Cardiovascular Diseases Using Different Intervals of ECG Signals			Set B (2s) Accuracy:99.80% Sensitivity:99.48% Specificity:99.93% Set C (3s) Accuracy : 99.84% Sensitivity:99.52% Specificity:99.95%
2021	Mahwish Naz, Jamal Hussain Shah1, Muhammad Attique Khan, Muhammad Sharif, Mudassar Raza, Robertas Damaševičius	From ECG Signals to Images: A Transformation Based Approach for Deep Learning	MIT-BIH & CUDB	AlexNet VGG16 SVM	MIT-BIH Accuracy: 97.6% CUBD Non
2021	Adyasha Rath, Debahuti Mishra, Ganapati Panda, Suresh Chandra Satapathy	Heart Disease Detection Using Deep Learning Methods From Imbalanced ECG Samples	MIT-BIH & PTB-ECG	LSTM GAN GAN-LSTM MLP NB SVM	MIT-BIH Accuracy: 0.992 F1-Score: 0.987 AUC: 0.984 PTB Accuracy: 0.994 F1-Score: 0.993 AUC: 0.995
2022	Khiem H. Le, Hieu H. Pham, Thao BT. Nguyen, Tu A. Nguyen, Tien N. Thanh, Cuong D. Do	LightX3ECG: A Lightweight and eXplainable Deep Learning System for 3-lead Electrocardiogram Classification	Chapman & CPSC-2018	1D-CNN ((Apply this method three times)) LightX3ECG	Chapman (Average) Precision: 0.9736 Recall: 0.9703 F1 score: 0.9718 Accuracy: 0.9873 CPSC-2018 (Average) Precision: 0.8209 Recall: 0.7862 F1 score: 0.8004 Accuracy: 0.9628
2023	Mou Wang, Sylwan Rahardja, Pasi Frnti, Susanto Rahardja	Single-Lead ECG Recordings Modeling for end-to-end Recognition of Atrial Fibrillation with Dual-Path RNN	CPSC-2018	DPRNN	Accuracy: 0.971 F1 score: 0.953
2023	Enock Khondowe, Xinzhong Zhu, Samantha Rusike, Mabasa Nyasha Mutyambizi	One-Dimensional CNN Approach for ECG Cardiovascular Disease Classification	MIT-BIH & PTB-ECG	1D-CNN	MIT-BIH Accuracy: 99.0% PTB-ECG Accuracy: 99.0%

5. Conclusion

The detection and treatment of cardiac disease may be revolutionized by artificial intelligence (AI). To find trends that might point to the presence of cardiac disease, AI-based algorithms can be used to evaluate enormous databases of medical data, such as electronic health records (EHRs). This can be used to find heart disease risk factors in patients before symptoms appear. Additionally, it can be used to create brand-new heart disease testing equipment and treatments. AI-powered imaging techniques, for instance, can recognize early indications of cardiac disease in images of the heart. AI can also be utilized to create medicinal therapies that are more efficient and have fewer negative effects than conventional treatments. Although the application of AI to the diagnosis and treatment of cardiac disease is still in its infancy, there is great promise for this technology to significantly improve the lives of those who already have the disease. It's possible that as AI technology advances, we'll see even more creative applications that help with heart disease detection and treatment. The most crucial elements related to the location of heart disease were discussed in this paper, along with the medical aspect, the significance of the researcher when developing any system for detecting heart diseases, the key techniques employed by researchers, the common data sets used by researchers, and an analysis of some studies that She had an influence on over the years.

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