AI and Cardiovascular Diseases: An Overview of Deep Neural Networks in Electrocardiogram Analysis

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Abstract

This paper gives an overview of the advancements in Artificial intelligence (AI) for the prognosis and treatment of cardiovascular disease (CVDs). AI techniques, inclusive of machine learning algorithms, have proven promise in analyzing medical photos for computerized detection of cardiac abnormalities and risk stratification. Decision-guide systems driven by way of AI useful resources in optimizing remedy strategies via leveraging patient facts for personalized interventions. Integration of AI with wearable devices and faraway monitoring structures allows real-time facts collection, early detection of cardiac activities, and powerful remote care control. However, demanding situations associated with information privateness, set of rules bias, and regulatory frameworks need to be addressed. Collaborative efforts amongst clinicians, researchers, and policymakers are crucial for harnessing the whole capacity of AI in CVD care.

I. Introduction

According to the World Health Organization, cardiovascular disease (CVD) is the most prevalent mortality determinant in the world, taking an estimated 17.9 million lives each year, which is approximately one-third of global mortality [1, 2, 3]. It is expected to account for more than 23.6 million deaths annually by 2030 [4]. More than four out of five CVD deaths are due to heart attacks and strokes, and one-third of these deaths occur prematurely in people under 70 years of age [1]. CVDs have become a major health issue negatively affecting the economic and social development of the whole world [4]. Cardiovascular disorders are considered to be serious health issues. Although there are various kinds of cardiac illnesses, heart diseases are the most common [5]. In the last ten years, traditional medication and surgery have been able to lessen the mortality rate and symptoms associated with CVDs; however, there is still a deficiency in clinical strategies for either repairing the damaged myocardium following myocardial infarction (MI) or averting the potentially fatal development of heart failure (HF). Conventional medicine is less intrusive but may harm organs or have other detrimental side effects. [4].

The early detection of cardiovascular diseases is one of the greatest difficulties facing physicians. This is due to several factors that affect health such as high blood pressure, increased cholesterol, abnormal pulse rate, and many other factors [5]. Therefore, utilizing and developing AI methods in the diagnosis of CVDs is crucial, as it can analyze the factors and predict the possibility of the disease, and increase the accuracy of the detection to more than 80% [5].

Machine learning techniques in the medical field have been expanding widely in recent years. The main idea of utilizing machine learning is to develop systems that can predict based on experience and stored data [5]. Some great examples of utilizing machine learning in the medical field include predicting and treating disease, providing medical imaging and diagnostics, discovering and developing new drugs, and organizing medical records. Deep learning is a subset of machine learning, where deep learning structures algorithms in layers to form an artificial neural network that can learn and make decisions on its own. The majority of artificial intelligence (AI) in our daily lives is powered by deep learning in one way or another. The difference between deep learning and machine learning is as follows: deep learning is capable of ingesting unstructured data in its unprocessed form (text, photos, etc.) and automatically identifying the set of characteristics that differentiate various data categories from each other, while machine learning relies more on human input to acquire knowledge [5]. The set of attributes that human experts need to distinguish between different data inputs is determined; often, this requires more structured data to learn.

A neural network with three or more layers is, by definition, a deep neural network, or DNN. Most DNNs actually have a lot more layers in practice. To identify and categorize occurrences, detect patterns and relationships, assess possibilities, and make predictions and judgments, DNNs are trained on vast volumes of data. A deep neural network has many layers that help improve and optimize the predictions and judgments made by a single-layer neural network, resulting in predictions and decisions that are more accurate. It is now possible to detect brain tumors using a type of DNN, with accuracy significantly lower than before. Furthermore, deep neural networks had a significant transformative effect on electrocardiogram (ECG) analysis. This paper comprises deep neural network techniques used in analyzing ECG signals for the prediction of CVDs, how it is done, and the effectiveness of using convolutional neural networks in ECG analysis.

Chapter Ⅱ provides information about AI applications in cardiovascular diseases, a brief explanation of ECG signals, and deep neural network models. Chapter Ⅲ comprises an explanation of the structure and mechanism of convolutional neural networks, while chapter Ⅳ discusses new technologies used in CVD diagnosis and AI outperforming prediction.

II. AI and Electrocardiograms

i. The potential of utilizing AI in CVD diagnosis

Digital healthcare encompasses the provision of tailored health and medical services, the utilization of electronic devices, systems, and platforms, as well as the integration of a wide range of medical services [6, 7]. By connecting healthcare with ICT (Information and Communication Technology), it can help to prevent, diagnose, treat, and manage diseases [7, 8]. The rapid advancement of Artificial Intelligence (AI) technologies has enabled healthcare professionals to increase their ability to process the vast amount of data generated through wearable devices used in the monitoring of patients' health [9].

This section provides an overview of the existing literature on the utilization of Artificial Intelligence (AI) to analyze wearable sensor data to predict and diagnose cardiovascular disease.

Wear-able devices

The utilization of wearable devices in the health sector is advancing rapidly, particularly in the areas of telemedicine, patient tracking, and mobile health systems. The utilization of these devices for remote monitoring and diagnostics of common cardiovascular diseases has been the subject of research [10]. Examining the potential and challenges of wearables [11, 12], specific barriers and knowledge gaps (HR and activity tracking) have been identified in the field of clinical cardiovascular healthcare wearables. The utilization of Artificial Intelligence (AI) and recent cutting-edge technologies has been extensively examined in all areas of Arrhythmia Care [9]. The Department of Drug Development (DL) has been a pioneering field of research for many years, and this paper provides an overview of the challenges and potential of this field in cardiovascular medicine [9]. End-to-end DL can also be used for resting ECG signal analysis to identify structural cardiac abnormalities, which can then be used to effectively screen symptomized populations [9]. Talking about risk prediction models in CVD, the biomarkers can be used for early detection of the disease as well as risk predictions [13].

Risk Prediction Models

A risk prediction model is a statistical regression model that relates the disease outcome with the characteristics of an individual. Risk prediction models are commonly referred to as risk stratification models or prognostic models. A risk prediction model typically includes multiple risk factors (or predictors) that are significantly related to the disease outcome. The association of a risk factor with the outcome of the disease is assessed based on the relative risk associated with that risk in the population, rather than in a single individual. A risk score may be calculated from a Risk prediction model for each individual, with a higher risk score indicating an increased risk of the disease. The risk score can be used to classify individuals into groups with different levels of risk of the disease. People in the high-risk groups are targeted for intervention strategies [14]. Discrimination refers to the ability of a risk prediction model to separate those who do and do not have the disease of interest [15]. This method is used to measure the likelihood of a risk prediction model assigning a higher risk score to a random sample of individuals who are expected to develop a disease within a specified time frame than to those who are not expected to develop the disease within that time frame. It was initially developed to assess the accuracy of classification in distinguishing signals from background noise in radar detection [14, 15]. A model with perfect discrimination will give higher predicted risk scores for all cases than for non-cases even if the predicted risk score does not match the observed risk.

ii. Electrocardiograms: properties and advantages.

Before delving into Electrocardiograms and their properties, a basic understanding of the heart must be achieved. The human heart operates mostly by intrinsic electric impulses. These impulses first arise in the sinoatrial (SA) node, located at the top of the heart's upper-right chamber (the right atrium), which is also known as the heart's “natural pacemaker.” These impulses flow through the heart through a process known as conduction where the impulses travel to the ventricles causing their contraction in a phenomenon known as ventricular contraction. This contraction is considered a representation of one heartbeat. In normal cases with no abnormalities, this rhythm is recorded as a sinus rhythm and is considered the basic rhythm of the heart.

This previously mentioned electrical activity can be recorded via a device known as an electrocardiogram. This device mainly records the starting point of these impulses and their conduction through the heart. An ECG is mainly administered to patients suffering from symptoms of CVDs such as blackouts or strokes as they're usually caused by an irregular heart rhythm. Electrocardiograms have various types depending on the condition that's being checked for. The most important types are the stress test, which monitors the heart during exercise to detect CVDs such as coronary artery disease; the Holter monitor, which monitors for longer periods; and the resting 12-lead ECG, which is used in a resting state and is considered the optimal type of ECGs. To record an ECG, electrodes must be inserted in the limps and chest to record different views of the heart. These views are called leads and the number of leads is not equal to the number of electrodes. For a full picture of the heart, a 12-lead ECG is optimal which is why 12-lead ECG tests are preferred.

To interpret the reading of an ECG, some basics must be understood. The ECG visualizes each ventricular contraction (heartbeat) by one ECG complex as shown in figure 1.

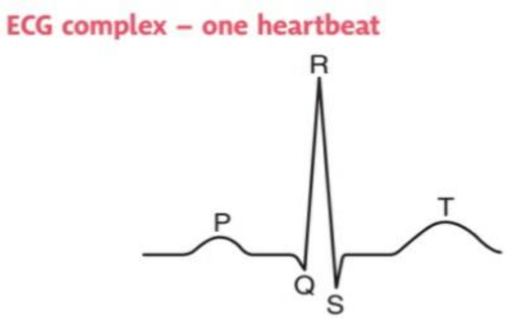

Figure 1: illustrating the ECG complex for a heartbeat

There are 5 main points in an ECG complex those being "P", "Q", "R", "S", and "T". The "P" wave shown here is a representation of the electrical activation of arterial muscle. The PR interval is the amount of time needed for the impulse to travel from the artery to the ventricle. The QRS complex symbolizes the spread of the impulse causing ventricular contraction. The ST interval showcases the full activation of the ventricles, while the "T" wave shows the return of the ventricles to a resting electrical state. Without any abnormalities, a normal beat should be a succession of one P wave, a QRS complex, and finally a T wave. The way those waves and intervals are displayed can tell a lot about the condition of the heart. For example, if the QRS complexes are compressed together, this indicates a higher heart rate. They can also indicate the rhythm of the heart based on how consistent QRS complexes are. Ideally, the reading of a healthy heart via ECG should look like figure 2.

Figure 2: illustrates a healthy heart rhythm

The professionals reading an ECG recognize certain patterns and rhythms that indicate different CVDs. For example, figure 3 shows a rhythm that indicates a complete heart block while figure 4 shows a pattern indicating acute ischemia [15, 16].

Figure 3: shows a complete heart block

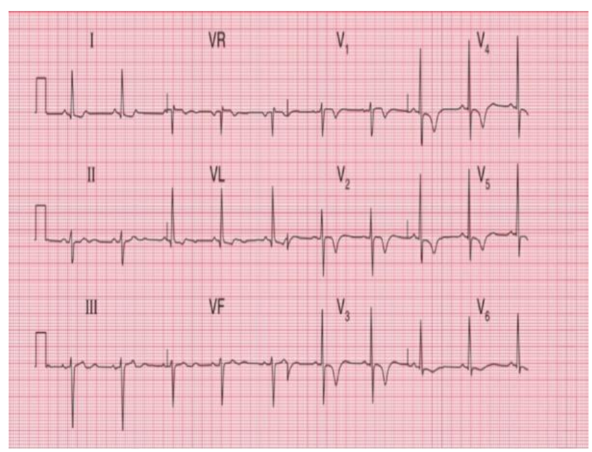

Figure 4: acute ischemia with T wave inversion

iii. Types of deep-learning models used in ECG analysis.

Deep learning (DL) is a class of machine learning that performs much better on unorganized or huge data with increased high-performance computing, which made it more popular at present. It focuses on creating and training complex neural networks to learn and make intelligent decisions from large volumes of data. Deep learning is called “deep” as it passes the data through numerous layers, where each layer can gradually extract features and pass the data to the next layer. The first layers extract low-level features, and the later layers combine features to create a comprehensive representation. Deep learning models are built using artificial neural networks, which are computational structures inspired by the organization of neurons in the human brain. These networks consist of layers of interconnected nodes (neurons) that process and transform data. Nowadays, deep learning is used in a lot many applications such as Google’s voice and image recognition, Netflix and Amazon’s recommendation engines, Apple’s Siri, automatic email and text replies, and chatbots [18].

Deep neural network models had a transformative impact on analyzing electrocardiograms. It led to many significant advancements such as improved accuracy, where some studies have experimentally demonstrated that deep learning features are more informative than expert features for ECG data [19] Several deep Learning (DL) models have been developed to improve the accuracy of different learning tasks, including Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Deep Belief Network (DBN), Generative Adversarial Networks (GANs).

- **Convolutional Neural Network (CNN):**

CNNs represent a class of deep neural networks (DNNs) that are widely applied for image classification, natural language processing, and signal analysis. A standard CNN is composed of several convolutional layers followed by a batch normalization layer, nonlinear activation layer, dropout layer, pooling layer, and classification layer [19]. Section III will focus on CNNs in detail.

- **Recurrent Neural Network (RNN):**

It has been widely used to solve tasks of processing time series data, speech recognition, and image generation, and recently, ECG signal denoising and ECG classification. RNNs, including variants like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), are suitable for sequence data like ECGs. They can capture temporal dependencies and patterns in ECG waveforms, making them useful for tasks such as heart rate prediction, rhythm classification, and anomaly detection. A typical RNN includes an input layer, a hidden layer, and an output layer, where at each time step, the RNN receives an input, updates its hidden state, and makes a prediction. While RNN is highly suitable for short-term dependent problems, it is ineffective in dealing with long-term dependent problems. That’s why the types mentioned long short-term memory (LSTM) and gated recurrent unit (GRU) were introduced to overcome the shortcomings of RNN [20, 21].

- **Multilayer Perceptron (MLP):**

The most popular supervised neural network, MLP, is successful in learning complex systems. Despite being variable, the MLP architecture consists of numerous layers of neurons coupled to one another in a feed-forward manner [20].

- **Generative Adversarial Networks (GANs):**

This type of model consists of two sub-models: a generative model G that captures the data distribution of a training dataset in a latent representation and a discriminative model D that calculates the probability that a sample generated by the generator comes from the true data distribution [21]. It can be useful in data augmentation or simulating abnormal conditions for training and testing classifiers. figure 5 illustrates the architecture of the GAN.

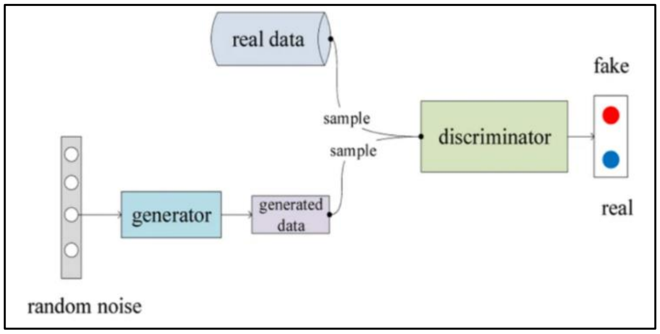

Figure 5: the architecture of GAN [21]

- **Deep Belief Network (DBN):**

DBN is a powerful learning model used to model evolving random variables over time. It is composed of multiple Restricted Boltzmann Machine (RBM) layers. The function of each RBM in a layer is to receive the inputs of the previous layer and feed the RBM in the next layer [20].

Figure 6 shows a brief comparison between DL models:

Deep Learning Model	Performance	Computational Requirements	Suitability for Flooding Scenarios
FNN	Good performance in capturing complex patterns and relationships	Moderate computational requirements	Suitable for both short-term and long-term flood forecasting
MLP	Effective in handling non-linear relationships	Moderate computational requirements	Suitable for general flood forecasting and management tasks
CNN	Excellent in capturing spatial information and patterns	High computational requirements due to convolutional operations	Suitable for analyzing flood-related imagery and spatial data
RNN	Suitable for time-series data analysis	Moderate computational requirements	Suitable for short-term flood forecasting and temporal analysis
LSTM	Superior in capturing long-term dependencies and handling sequence data	Moderate computational requirements	Suitable for both short-term and long-term flood forecasting
GRU	Similar to LSTM, effective in capturing long-term dependencies	Lower computational requirements compared to LSTM	Suitable for real-time flood forecasting and analyzing time-series data
GAN	Suitable for data generation and augmentation	High computational requirements, especially for training	Suitable for enhancing data availability and training robust flood prediction models
SOM	Effective in clustering and visualizing data patterns	Moderate computational requirements	Suitable for exploratory analysis and data visualization in flood management
Auto-encoders	Useful for feature extraction and dimensionality reduction	Moderate computational requirements	Suitable for preprocessing and extracting relevant features from flood-related data
DNN	Versatile and can be applied to various flood forecasting tasks	Computational requirements depend on the model complexity	Suitable for different flood scenarios based on problem-specific adaptation
DTL	Utilizes pre-trained models for transfer learning	Computational requirements depend on the pre-trained model size	Suitable for scenarios with limited labeled flood data and knowledge transfer
BM	Effective in unsupervised learning and pattern recognition	High computational requirements for training complex models	Suitable for unsupervised feature learning and anomaly detection in flood events
IR	Primarily used for data retrieval and analysis	Low computational requirements	Suitable for retrieving and analyzing flood-related information from textual and unstructured data

Figure 6: DL models comparison

III. Convolutional AI in ECG Analysis:

I. Convolutional neural networks (CNNs) and their applications.

As mentioned previously, CNNs are the most prominent category of neural networks, especially in high-dimensional data like images and videos. It falls under the supervised learning category of neural networks. CNN is a multi-layer neural network, which consists of multiple back-to-back layers connected in a feed-forward manner [20, 22]. It is stimulated by the neurobiology of the visual cortex, which contains convolutional layer(s) pursued by fully connected (FC) layer(s), with the probability of the existence of subsampling layers between these two layers [22]. The main layers include the convolutional layer, normalization layer, pooling layer, and fully-connected layer, as shown in figure 7. The Three first layers are responsible for extracting features, while fully connected layers are in charge of classification. Thus, the primary application of CNN exists in databases, where the number of nodes and parameters required to be trained is comparatively large [22].

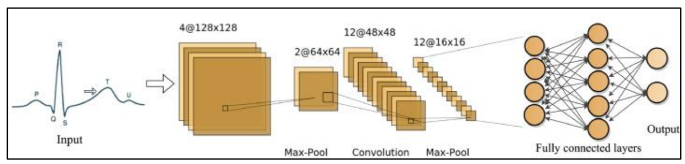

Figure 7: illustrates the architecture of CNN [20].

Here is its structure in more detail:

- **Convolutional layer:**

The convolutional layer plays a vital role in the operation of CNNs. It is the main building block that determines the output from the given input. This output is achieved through a feature detector, which is known as a **kernel**. Before understanding what a kernel does, it should be taken into consideration that any digital image consists of a matrix of pixel values from 0 to 255 (channel), where zero corresponds to black color and 255 to white color. In a typical digital camera, an image consists of 3 of these channels, each one corresponding to one of the RGB colors (red, green, blue). A kernel is a matrix with initial values. When the data hits the convolutional layer, the layer convolves the filters over the height and width of the information data, and while that it computes the dot product between the input and filter values of each matrix (which are the initial values of the kernel), therefore building a 2-D activation map of that filter [22, 23]. Figure 8 visualizes this process. “From this, the network will learn kernels that ‘fire’ when they see a specific feature at a given spatial position of the input, which is known commonly as activations” [23]. Each kernel will have an associated activation map, which will be stacked along the depth dimension to create the convolutional layer's whole output volume [23].

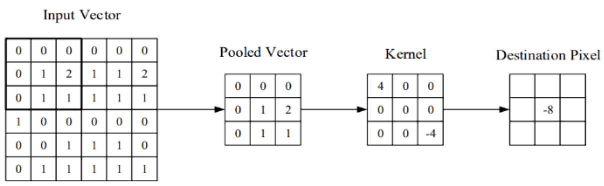

Figure 8: a visual representation of a convolutional layer [23].

- **Pooling layer:**

The main aim of this layer is to reduce the dimensionality of the maps, by keeping the most important parts and discarding the rest, therefore decreasing the parameters, the time complexity of the model, and the probability of overfitting [23]. In this stage, each activation map in the input undergoes scaling its dimensionality using the “MAX” function by the pooling layer. Max-pooling layers are the most common pooling layers, where they have kernels of a dimensionality of 2 × 2. “This scales the activation map down to 25% of the original size - whilst maintaining the depth volume to its standard size” [23].

- **Fully connected layer (FC):**

The FC layer is a typical deep NN, where it consists of directly connected layers of neurons, with no other layers connected in between them [23]. In other words, each neuron in each layer is connected directly to each neuron in the two adjacent layers to this layer. The aim of this layer is to build predictions from the activations to be classified into categories and to associate features to each particular label. Figure 9 shows a simple CNN architecture.

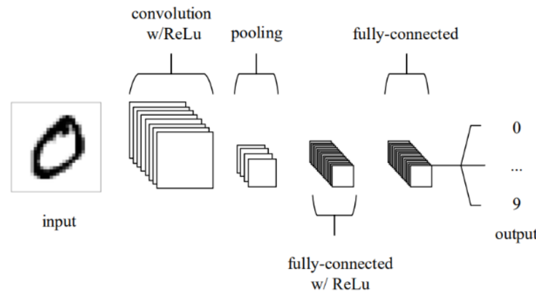

Figure 9: CNN architecture [23].

II. Discuss how CNNs are adapted for ECG analysis.

The analysis has three main steps: data preprocessing, feature extraction, and classification. The ECG signal is characterized by high noise and high complexity, therefore during the preprocessing stage, the signals are denoised and padded or cut into segments with equal sizes. In feature extraction, features can be extracted from the morphology of the ECG signal in the time and frequency domain or directly from the heart rhythm [24]. The time domain feature is the analysis of mathematical functions, data, and signals with respect to time, while in the frequency domain feature, instead of considering how a signal changes with time, the focus is on the various sinusoidal components that make up the signal. The spectrum frequency is found by applying a fast Fourier transform to the time domain signal, where there are some spectral features that should be used for CVD classification, which include the main frequency peak, the spectral component with maximal power content, and the spectral content below the main peak. An ECG is a 1-D signal, so it can be fed directly into 1-D CNN or transformed into an image and processed by 2-D CNN, depending on the specific purpose of analysis [24]. The convolutional filters of the convolutional layers extract features from the ECG signal. Convolutional filters slide across the signal, capturing local patterns such as QRS complexes and ST-segment changes. Max-pooling or average-pooling layers reduce the spatial dimensions of the feature maps, focusing on the most important information. Finally, fully connected layers are used to classify signals into different types of heartbeats or diseases according to the features extracted [24]. CNNs are trained using labeled ECG data, where each segment is associated with a specific diagnosis.

Detecting Myocardial Infarction (or heart attacks) using CNNs:

In this study, CNNs are used to detect myocardial infarction (MI) without relying on the detection of ST deviation or T peak and without extracting handcrafted features. Instead, it utilizes continuous wavelet transform and a CNN architecture to process the ECG data as 2D images. The ECG signal is divided every five seconds and normalized to the normal distribution. "The data segment is passed to a continuous wavelet transform with bior1.5 mother wavelet and scale from 1 to 256" [25]. This transforms ECG signals to be processed by the CNN as 2D data instead of 1D signals. This 2D data is mapped to RGB images with sizes 256 * 256 to serve as the input for the CNN [25]. The CNN architecture includes Two convolutional layers, two max-pooling layers, two ReLU activation layers, two fully connected layers, and a softmax layer for classification. The study reports a sensitivity (true positive rate) of 92.04% and a specificity (true negative rate) of 82.85% for the proposed CNN-based method. In conclusion, the findings suggest that the learned features in the convolutional layers are promising for extracting relevant information for MI detection.

III. Benefits of CNNs in ECG analysis

As already discussed above, the ECG is a powerful tool in the hands of cardiologists as it can lead them to detect premature cases based on analysis of the formed waves. While this is a very common method in ECG analysis, it can lead to a variety of human errors that can cost people their lives. This is the reason that research into CNNs, as discussed above, has been heavily leaned on. The exact reason that a deep learning AI like CNN trumps humans is that its interpretation heavily differs from one cardiologist to another. This is because humans can interpret the different signals and rhythms differently due to either different backgrounds and experiences, not taking sex, age, and ethnicity into account, or being biased towards one view before analyzing the test. The CNN algorithm takes all the previous into account as it can conclude certain phenotypes through a patient's electrocardiogram reading thus rendering itself superior to an average cardiologist, or experts in some cases, as will be proven later in this paper [26].

While it is proven that CNNs perform better than human cardiologists [27], what makes them stand out against other AI algorithms? First of all, computer-generated analysis of ECGs had been done before by cardiologists, but it was severely limited in what it could detect because it had to be fed manual recognition algorithms and was bound by rules set in stone. This is a problem as ECGs vary greatly from one person to the other thus these systems couldn't fully process all input information. Not only that, but the input fed to the system by humans gave rise to random and systematic errors in calculations. CNNs, on the other side, are fully automated and reach an accuracy similar to that of experts due to their ability to self-learn as discussed before [26]. Additionally, CNNs are fed tons of inputs that are labeled by humans. These inputs often have correlations with certain CVDs that have not been discovered by experts yet. This allows CNNs to put these pieces together and offer a level of analysis way higher than that of expert cardiologists. Lastly, the ability of CNNs to self-learn means that the more input, in this case, patients' readings, the more it learns about CVD patterns thus improving its ability to detect premature cases [28].

In an attempt to prove the practicality of CNNs in ECG analysis, some researchers [28], created a CNN algorithm and fed it with information that's held in most institutions and then combined each institutional databank with the other to allow the CNN to have enough data. This data was then analyzed by expert cardiologists and was then extracted. The CNN was then fed 38 repeating patterns that are the most relevant in ECG diagnosis.

The CNN was then tested using 38 samples of those same patterns and the results were as shown in figure 10.

Table 1. Performance of the CNN on 38 Diagnostic Classes Compared With Cardiologist Clinical Diagnoses in the Holdout Test Data Set (N = 32 576 Patients; 91 440 ECGs)

Diagnostic class	Frequency	CNN AUC (95% CI)	Specificity[a]	Sensitivity[b]
Rhythm				
Sinus	57 186	0.995 (0.994-0.995)	0.993	0.990
Atrial fibrillation	6572	0.997 (0.997-0.997)	0.994	0.999
Atrial flutter	1406	0.991 (0.990-0.993)	0.980	0.986
Ectopic atrial rhythm[c]	514	0.949 (0.938-0.961)	0.900	0.899
Atrial tachycardia[c]	194	0.967 (0.958-0.975)	0.899	0.897
Ventricular tachycardia[c]	33	0.995 (0.989-0.999)	0.986	1.000
Junctional rhythm[c]	489	0.979 (0.973-0.984)	0.960	0.953
Supraventricular tachycardia[c]	308	0.996 (0.994-0.997)	0.994	0.990
Bigeminy[c]	248	0.989 (0.980-0.995)	0.993	0.976
Premature ventricular complex	3930	0.964 (0.960-0.967)	0.947	0.920
Premature atrial complex	4633	0.977 (0.974-0.979)	0.966	0.968
Ventricular paced	2443	0.997 (0.996-0.998)	0.995	0.998
Atrial paced[d]	557	0.993 (0.988-0.997)	0.997	0.984

Figure 10: shows a sample of the results of the ECG CNN analysis

This high rate of specificity and sensitivity shows that CNNs are highly viable in CVD diagnosis as they were quite high, especially for rhythm and conduction diagnosis. The CNN also showed high AUCs (area under the curve) of at least 0.96 for 32 out of 38 diagnoses. The system only faced exceptions in ectopic atrial rhythm, nonspecific interventricular conduction delay, prolonged QT, and posterior infarct [28].

The CNN system also proved successful in detecting 2 dangerous CVDs in the form of Atrial fibrillation (AF) and Human Cardiac Fibroblasts (HCF). AF is a CVD that increases the risk of strokes, heart failure, and ER visits. The danger of AF is only worsened by the fact that 20% of the affected are asymptomatic. A group of experts performed an experiment where they used a CNN fed with data from about 126,000 patients that were validated by experts. Patients were then tested for their sinus rhythm which was analyzed by the ECG. Any case that was flagged by CNN in the first 31 days was considered AF positive. In the end, the results were a sensitivity of 79.0%, a specificity of 79.5%, and an accuracy of 79.4% in detecting AF patients using the input data thus recognizing AF in its unrecognizable stages. The case with HCF is similar. HCF is a highly malignant CVD that can cause premature death. The problem with manual ECG analysis of HCF is that its readings are non-specific and are indistinguishable from other CVDs. After a CNN had been fed data from 2,500 patients and about 50,000 control samples, the ECG was able to diagnose HCF using its ECG reading without the more commonly used methods of echocardiography combined with the clinical history. After being tested with 612 HCF patients and about 13,000 control samples, the CNN reached a sensitivity of 87% and specificity of 90% [26].

While CNNs have a high advantage over cardiologists [27], experts, and other AI methods, they have their shortcomings. The first one is data control. Data control is essential for a CNN to facilitate the quality of the input data which in turn would affect the output data. So, feeding a CNN with correct, supervised, and reviewed data is essential in developing a CNN algorithm. The databank also has to be severely secure to avoid corruption of the data from third parties. Finally, CNNs are considered black boxes. Black boxes are models that are not 100% understood by humans as they cannot pinpoint the methodology the CNN uses to reach its output thus detrimenting the ability of human assists [27].

IV. Autocardiogram necessity

i. Integration with new technologies: body sensors, MRI, echo, and more

The utilization of cutting-edge technology has become increasingly pertinent in the treatment and diagnosis of cardiovascular disorders [29]. Body sensors are one such technology that can be used to monitor and measure heart and vascular health parameters [29]. These devices, such as smartwatches or wearable devices, are placed on the body and collect data such as heart rate, physical activity level, and stress levels [29]. Medical professionals can utilize this information to evaluate cardiac health and modify treatment regimens [29]. Magnetic Resonance Imaging (MRI) is also utilized for the diagnosis and monitoring of heart and vascular disorders [30]. Magnetic resonance imaging (MRI) provides a comprehensive view of the cardiac anatomy, enabling visualization of the internal organs and vessels to detect any alterations or anomalies [30]. This data can be utilized to create tailored treatment plans and track patient progress [30]. Echography is a medical procedure that utilizes sound waves to generate visual representations of the cardiovascular system and blood vessels [31]. Medical professionals can visualize cardiac activity, assess cardiac function, and comprehend the cardiac anatomy [31]. Echo is also capable of determining the size and functionality of the heart's atria and chambers, as well as diagnosing conditions such as coronary artery stenosis and defective heart valves [31]. In the field of cardiovascular disease, these cutting-edge technologies are utilized to enhance diagnosis and provide clinicians with precise information about patients' health conditions, enabling them to implement effective treatment plans [29]. The integration of these technologies with pertinent medical data is essential for providing cutting-edge and efficient care to patients with cardiovascular disease [29]. This integration is constantly being developed and is anticipated to lead to future advances in patient treatment and care [29].

ii. AI-analyzed ECGs: Accurate decision-making and complications prediction

Electrocardiogram (ECG) analysis is a way of assessing and tracking cardiac hobby by studying the electrical indicators produced in the course of cardiac cycles [32]. The development of generation and the fast advancement of Artificial Intelligence (AI) have enabled the usage of AI inside the interpretation of ECGs for the motive of creating particular selections and predicting complications in cardiovascular diseases [33]. Artificial Intelligence-primarily based ECG analysis makes use of the training of AI models primarily based on earlier affected person information and complicated algorithms to process the data and extract pertinent statistics [33]. Data are gathered from an extensive populace of patients with cardiovascular issues and evaluated via trained fashions [33]. These models benefit from insight from data and increase state-of-the-art understanding of styles and records that may be accrued from ECG recordings [33]. Artificial Intelligence-Superior Electrocardiography (ECG) can offer good-sized blessings in the treatment of cardiovascular problems [33]. For example, they may be applied to make precise diagnoses, examine capacity dangers, and suggest appropriate remedy courses [33]. Due to its capacity to manage big volumes of statistics and to become aware of patterns and unique traits, AI-assisted ECG analysis can provide precise effects and enable healthcare professionals to make informed and well-timed picks [33]. In addition, the usage of Artificial Intelligence (AI) to analyze ECG facts can help in the identification of capacity headaches related to cardiovascular sicknesses [33]. The ECG statistics can then be analyzed by using artificial intelligence-trained fashions to stumble on unique characteristics and trends that propose the chance of complications, consisting of acute coronary syndromes [33]. This can facilitate timely diagnosis and treatment to save you headaches and decorate treatment effects [33]. Artificial Intelligence-primarily based Electrocardiograms (ECGs) are a first-rate step forward in the remedy and analysis of cardiovascular sicknesses, allowing clinicians to make informed choices concerning remedy, diagnosis, and diagnosis of capability complications [33]. This technology allows scientific professionals to enhance patient consequences and enhance first-rate care for those laid low with cardiovascular problems [33].

V. Conclusion

After reviewing multiple research papers and filling in others' gaps, the paper was able to deduce the validity of AI-aided ECG analysis. It was first concluded that autonomous analysis of an electrocardiogram using a deep-learning AI method called a convolutional neural network. This method proved a high success rate as it successfully deciphered the patterns of the ECG and their implications. Not only that but it was able to accurately detect cardiovascular disease at a higher success rate than cardiologists and much earlier. It also proved to be able to interact with IOT technologies such as body scanners and smartwatches to offer 24/7 tracking of the human heart without intrusion or discomfort and at great accuracy. Finally, it was able to perceive complications due to CVDs before their occurrence and prevent the advancement of the disease. While it is not known when this technology will be widely available to the public, it has without a doubt proven itself. Also while this tech is highly accurate and precise, it takes years to train the algorithms responsible for it, which might render it highly impractical until a database is established.

VI. References

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