A Systematic Review of Deep Learning Techniques for ECG Arrhythmia Classification

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***Abstract*— The use of Deep Learning (DL) methods for detecting arrhythmias from ECG data, focusing on their clinical potential while highlighting areas that need more research for reliable application. The study stresses the importance of using diverse ECG datasets, advanced noise reduction, data augmentation, and new integrated DL models for better accuracy in clinical settings. Specifically, the authors introduce a hybrid model that combines Convolutional Neural Networks (CNN) with Variational Autoencoders (VAE) — the first use of VAE for classifying 1-D ECG signals. This model uses both supervised and unsupervised learning and shows better performance compared to standard CNNs and Autoencoders (AEs), particularly in reducing errors in diagnosing different cardiovascular diseases (CVDs). The paper also addresses challenges like data imbalance, which can be improved by using real-time data and augmentation techniques, thereby increasing model accuracy. Furthermore, In some paper we come across developing a mobile app based on this CNN-VAE model, which could help healthcare professionals predict high-risk CVD patients. The review also covers successful DL algorithms, such as GRU, LSTM,DBM,BiLSTM and CNN, which have proven effective in classifying arrhythmias like atrial fibrillation and ventricular ectopic beats. The study highlights the importance of selecting the right DL algorithm to achieve optimal classification results.**

***Keywords*— ECG, diagnostics, clinical decision support, CNNs, DBM, hybrid DL, RNNs, including LSTM and BiLSTM, GRU.**

I. INTRODUCTION

With the use of ECG tracing, clinicians may quickly and accurately diagnose patients by using an event or arrhythmia classification approach, which can extract vital information about the patient's heart based on heart rate and heart rhythm. Prior to diagnosis, the ECG must be entered in high-resolution (HR) format. Here, a greater sample frequency is shown by the high resolution. This is because sampling frequency and signal quality are often correlated. The signal's constituent parts will be more faithful at higher sampling frequencies . In situations where the diagnostic unit does not get such HR data, signal reconstruction becomes a crucial duty[1]. In any communication system, signal reconstruction is a frequent difficulty. Signal reconstruction is a must for all forms of communication, including mobile and satellite. Data processing plays a crucial role in auxiliary medical devices such as electrocardiograms (ECG), magnetic resonance imaging (MRI), and computed tomography (CT) that use it to assess a patient's condition. Taking the National Aeronautics and Space Administration (NASA) as an example, the agency's long-term expedition strategy encourages human explorers to travel on extended missions, which will make it more important to maintain good health in situations involving harsh conditions, like low gravity and increased radiation exposure.

[2]. Astronauts have more difficulties because of these conditions, which include radiation exposure, decompression sickness, and metabolic stress. It is crucial to keep an eye on the astronauts' condition in the spacesuit to support their performance and well-being. Also, an enormous amount of biomedical signals gathered from the body are used to continually check their state of health. One of the key constraints in space continues to be the duration and power required for data transmission. Therefore, finding methods for making effective use of time and energy for communication is essential. The majority of biological signals either have a sparse representation in another domain or are intrinsically sparse[3]. The Nyquist sampling rate is used to extract the digitally formatted biological signals from analog to digital converters.

In the field of event categorization, several approaches from traditional to cutting-edge deep learning application have been developed. Many deep learning-based methods, such as deep belief networks (DBN), convolutional neural networks (CNN), gated recurrent units (GRU), long-short-term memory (LSTM), and recurrent neural networks (RNN). It became evident from the many studies that were published up until 2018 that CNN is the preferred technique for feature extraction. The LSTM, CNN, and GRU/LSTM were successful in classifying cardiac arrhythmias such as atrial fibrillation, ventricular ectopic beats, and supraventricular ectopic beats[4].

II. METHOD USED IN ECG IN HEALTHCARE

The network designs have been suggested in this paper:

1. Super Resolution ECG-SRCNN Network
2. 1D-CNN network for categorizing ECG events
3. Deep Learning (DL) and Electrocardiogram (ECG)
4. Convolutional Neural Network (CNN) and ECG
5. Deep Neural Network (DNN) and ECG
6. Recurrent Neural Network (RNN) and ECG
7. Gated Recurrent Unit (GRU) and ECG
8. Deep Belief Network (DBN) and ECG)
9. Long Short-Term Memory (LSTM) and ECG

ECG-SRCNN, a deep-learning-based super-resolution network, is designed to handle sufficient signal reconstruction tasks while retaining the key characteristics of the low-resolution (LR) version. The proposal for ECG event categorization in the second half is based on a deep learning architecture called 1D-CNN. a GRU-based RNN-based framework that recognizes anomalous cardiac events and learns the typical ECG behavior[5]. Two distinct scenarios were examined for this: identifying various noise artifacts and cardiac events brought on by certain diseases.

III. PURPASS AND SCOPE OF REVIEW

Atrial fibrillation is one of the main arrhythmias seen in the medical sector (AFIB). Nurmaini et al. (2020) provide an automated AF detection system that utilizes the 1D-CNN model to process a tiny strip of ECG data. With 99.98% accuracy, In order to differentiate between three classes—AF, non-AF (NAF), and normal sinus rhythm (NSR)—this system combines the advantages of 1D-CNNs and discrete wavelet transform (DWT) [6]. In essence, the goal was to use millions of low-resolution and high-resolution picture patch pairings to teach a computer how to upscale a low-quality image by exposing it to a vast collection of sample photos [7].By merging U-Net and LSTM layers, Busty and Grau (2018) create an SR network that can handle temporal information from dynamic cardiac cine MRI data, using the dynamic character of temporal data. An HR sequence was produced using this technique from a set of long-axis, low-resolution photos [8].Experts from all around the world have also taken a lot of intriguing steps in the field of audio processing. The Kuleshov et al. (2017) model is trained using matched low- and high-quality audio samples. Our model uses an interpolation approach similar to the picture super-resolution during testing to forecast missing regions inside a low-resolution signal [9]. Mousavi et al. (2015) describe a method for signal identification and recovery based on stacked denoising auto-encoders (SDA). The model used in this study uses both linear and somewhat non-linear data, which is different from the case in CS. The model creates a structured representation and produces a signal estimate using the training data [10].

Chronic illnesses that are frequent and seriously dangerous to human health include cardiovascular diseases (CVDs) [1]. An electrocardiogram (ECG) is a noninvasive method for monitoring variations in the bioelectric activity of the heart. An ECG equipment might monitor the patient's heart's cyclical contractions and relaxations by using electrodes applied to their skin. Typical ECG signals are made up of several waveforms, such as P, T, and QRS complex.To detect cardiac abnormalities in the course of routine medical care. Cardiologists typically do ECG screenings for patients as part of their regular medical practice to detect cardiac anomalies and effectively treat such conditions. This process involves extensive human labor and costly medical procedures[11].

Rebuilding signals with pulses of different widths is a very difficult process. Baechler et al. (2017) showed a sampling method and properly reconstructing Lorentzian pulses of varying widths using a series of theorems. In this case, the reconstruction work is tailored to fit the usual finite rate of innovation (FRI) machinery. Diracs are the fundamental building block of the original FRI theory. This signal model's constituents are referred to as variable[12].

Recent applications of deep learning (DL) in medical diagnostics have shown remarkable results, including the automated classification of heart problems using ECG data. Multiple sensory neural layers in deep learning (DL) models can be used to define the learned mapping from ECG data to relevant medical categories. By using training datasets to adjust the neuron weights in order to reduce the discrepancy between the ground-truth categories of the training data and the inferred categories, the DL model's inference power is enhanced [5]. Because DL-based ECG classification has a powerful multi-level abstraction, it may be able to transfer the features of ECG signals to their respective categories more successfully than conventional machine learning-based classification methods like support vector machines (SVM) and clustering. DL-based categorization of arrhythmias using ECG data is reviewed in this research. Diagnosing diverse forms of arrhythmias poses a unique clinical challenge for practicing cardiologists. However, the context and goal of the classification methods for arrhythmia categories are the same when examining the classification task using DL, which is to precisely map the ECG's characteristics to the appropriate categories. Thus, the general research state, difficulties, and prospects for deep learning-based arrhythmia classification are the main topics of this review[13].

Models developed on particular ECG datasets may not perform well in real-world situations due to the wide variation in ECG signals among individuals and the significant reliance of deep learning techniques on data distribution in the feature space. When identifying ECG arrhythmias, we take into account a number of factors during the whole DL procedure because many assessments that have already been published [14] only address DL approaches. In particular, the following are our main contributions.

The DL-based arrhythmia classification with ECG signals is comprehensively analyzed in terms of the ECG database, preprocessing, DL approach, evaluation paradigm, performance metrics throughout the DL workflow, and code availability of the studied articles. The historical road map is reduced by examining the pattern of techniques in each place during the last several years.

IV. METHODOLOGY

In order to include more candidate studies and avoid missing studies for arrhythmia classification—many studies fail to specify their classification goals—we first created a crude search. Consequently, the following search phrases have been selected for the literature search: ECG OR electrocardiogram AND CNN OR recurrent neural network OR RNN OR LSTM AND deep learning OR deep neural network OR convolutional neural network.

A. Data Extraction

This research covers a wide range of subjects, such as general data, ECG databases, preprocessing, the DL technique, the assessment paradigm, performance measures, and code accessibility. A detailed explanation of the information gleaned from those elements is provided below.

1.General Information: A synopsis of the chosen studies' publications, including the journals or conference proceedings in which they were published and the years of publication, is given.

2.ECG Database: For well-known ECG databases used for arrhythmia classification, publication data, ECG signal data, and demographic data are examined;

3. Preprocessing: This section summarizes two popular preprocessing methods, namely data augmentation to address unbalanced datasets and denoising to eliminate artifacts.

4. DL Methodology: Each chosen publication's employment of DL methods is examined and summed up. It is addressed how to optimize for arrhythmias and the many kinds of DL models that exist.

5. Evaluation Paradigm:There are intra- and inter-patient paradigms for data-driven ECG diagnosis, depending on how patient ECG data is organized for training and testing..

6. Performance Metric: Metrics such as sensitivity (Sen), false positive rate (FPR), positive predictivity (Ppv), and $F1$ score of the selected research are discussed in detail, along with widely used metrics like total accuracy;

7. Code Accessibility: Comprehensive details on studies that release their code are provided, along with a list of the code's source.

B. Preprocessing

Preprocessing is frequently used on ECG data before importing them into deep learning models. This can enhance learning effectiveness and lower the computing cost of DL models [15]. The preprocessing stage is examined in this study from two perspectives: data augmentation and denoising. Both of them cope with unbalanced datasets and noisy ECG signals, which are frequent occurrences in actual clinical settings.

C. Denosing

ECG data can be distorted by bioelectrical interference, such as muscle activity and power line noise, as well as background noise. The ECG signals may be cleaned using the denoising method to remove overpowering micro characteristics, allowing DL models to concentrate more on the ECG features.Conventional denoising filters, including bandpass, notch, and lowpass filters, operate under the assumption that usable signals and noise exist in distinct frequency ranges. Additional denoising filters include of adaptive filters and smoothing filters like the median and Savitzky–Golay (S-G)[16] . ECG signals might be projected into the time-frequency domain using the discrete wavelet transform (DWT), which is based on wavelet basis functions The wavelet coefficients at high-frequency bands can be set to zero, or the modest wavelet coefficients can be thresholded to zero, assuming that the usable ECG signal is equal to the chosen wavelet basis function. [17]. For noise reduction, a variety of denoising techniques can be used in conjunction. This kind of approach will, however, result in increased processing delay.Over the past several years, there has been a rise in the quantity of works that explore denoising. Because they are simpler to use and more successful than the other two denoising techniques, the conventional filter-based approaches are more often used shown in Figure 1. Furthermore, a growing body of research has examined wavelet-based techniques for ECG signal denoising in recent years[18].

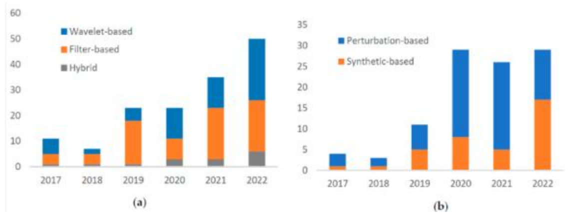


Figure 1: Preprocessing techniques used by selected research projects by year, broken down into two categories: (a) Denoising technique trends; (b) Data augmentation technique trends.

D. Data Augmentation

Data argumentation tools [19], which are utilized to get more training instances during the data preparation step, are the focus of this paper. Because aberrant signals are more difficult to produce, ECG data occasionally has biased distributions of abnormal categories that are noticeably less than normal categories. Inherently, DL models trained on the unbalanced ECG dataset will prioritize majority categories over minority categories, leading to biased learning. The augmentation techniques fall into two groups: synthetic-based techniques (36%) and perturbation-based techniques (64%, 65 out of 102). More data samples can be added to the ECG dataset for perturbation-based techniques by changing or perturbing the original samples in the same dataset, such as scaling and moving ECG waveforms or adding artificial noise[20].

Data sample perturbation is the process of collecting new data samples in the feature space that are similar to the original data samples. As a result, there can be a strong correlation between the new data samples and the original samples that were used to disturb the new data. In order to increase the number of minority categories, the artificial minority oversampling. Synthetic-based approaches, on the other hand, generate synthetic ECG data by either producing ECG signals that closely mimic genuine ECG properties or linearly combining real data samples. To expand the minority categories, the synthetic minority oversampling technique (SMOTE) and its variations, including SMOTENN, Borderline SMOTE, and SVM-SMOTE [21], are commonly employed. Recently, deep learning techniques like the convolutional neural style transfer network have been used to create synthetic data.

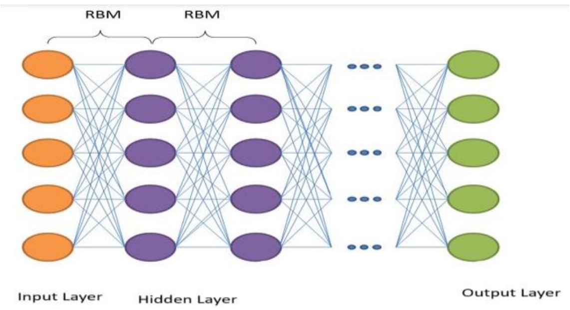
E. Model Methodology

It is possible to classify the DL classification models in the chosen research into the following groups based on the inherent characteristics of the major feature extractor in the neural networks: CNNs, recurrent neural networks (RNNs), including bidirectional LSTM (BiLSTM) and long short-term memory (LSTM), DBM, GRU, hybrid DL (a combination of several DL models).Below is a comprehensive examination of several DL models for ECG arrhythmia classification.

a) CNN

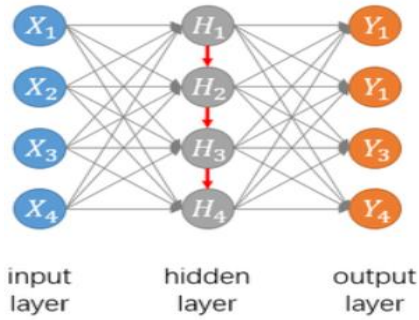
CNN is a deep learning model that is often used in natural language processing, signal analysis, and picture classification. Typically, each CNN layer includes a convolutional filter and pooling techniques to extract local and global characteristics [22]. In the spatial domain, CNNs may be categorized as either 1D or 2D based on the number of filtering directions they have. In particular, 1D CNN's filters go in one way, whereas 2D CNN's move in two filtering directions, or feature dimensions. ECG data with a single feature dimension, whether raw or denoised, is often a good fit for 1D CNN. ECG data with a single feature dimension, whether raw or denoised, is often a good fit for 1D CNN. For example, [23] introduces a flexible 1D CNN that eliminates the need for manually generated feature extraction for anomaly detection and ECG classification at any sampling rate of the ECG data.

Using 2-s ECG signal segments, a model input of lightweight 1D CNN with depth-wise convolutions and channel shuffling over the group is constructed. In [24], the 1D CNN is used to categorize 2, 5, and 20 different forms of heart illness, with few-shot learning to account for the limited size of the dataset. The spectrogram of an ECG, on the other hand, are examples of image-like input that 2DCNN largely takes into account. A conventional 2D CNN known as AlexNet [25] is used to recognize ECG data. Plotting 1D ECG recordings instantly converts them into 2D grayscale images that are 15 x 15. These photos are then used as input by 2D CNN. Multi-scale characteristics are extracted from a multi-lead ECG as matrix input by a multi-lead CNN using sub-2D convolution and lead asymmetrical pooling in [26]. Because 1D CNN operates more simply than 2D convolution, it frequently has less learnable parameters and performs computations more quickly. As a result, it is more appropriate for real-time ECG categorization and simpler to integrate into hardware.



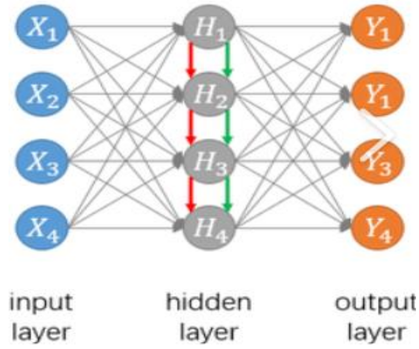
b) RNN

A deep learning framework that handles input as a time series is called an RNN. The temporal correlation within ECG signals may be utilized to ascertain the sign of their categories because they are time series. Conventional RNNs employ both the current input and information from the prior time instance to decide what information is in their hidden layer at any given time [27]. Because the RNN is more sensitive to temporal components this technique is useful for detecting buried temporal information in ECG feature circuits.



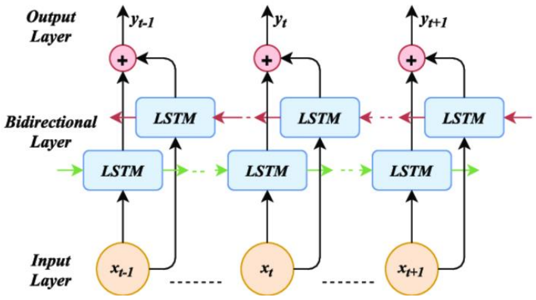
c) LSTM

Due to its superior time series analysis capabilities, the long short-term memory (LSTM) is becoming more and more popular than the traditional RNN The three gate topologies—forget, input, and output—that control the information flow in stored memory cells are found in the LSTM. Because the LSTM preferentially gathers significant information from prior inputs, it can process longer signal sequences than the RNN. A 6-layer LSTM is built in [28] to use ECG patterns to automatically recognize PVC beats.



d) BiLSTM

Two LSTMs that go through the input sequence in the forward and reverse temporal directions, respectively, make up a type of LSTM known as a bidirectional LSTM (BiLSTM) [29]. As a result, it may extract both causal and noncausal temporal dependence information from signals in order to enhance classification performance. The BiLSTM model classifies ECG data by employing recovered ECG wave statistics in the temporal dimension, such as the RR interval, QR interval, ST segment beginning point, and Q- and R-wave amplitudes. A 2D BiLSTM is utilized in [30] to identify AF from an ECG signal spectrogram, using the frequency components of each time event serving as input features.



e) Hybrid DL model

To classify ECG arrhythmias, many research advocate integrating multiple deep learning models into a single DL network. For example, [31] uses CNN and RNN to build an encoder-decoder system for categorizing heartbeats. CNNs are used to extract features, whereas RNNs are used to classify features. Additional instances of combining CNN with LSTM and BiLSTM, wherein CNNs are positioned in front of the modules for LSTM and BiLSTM in order to extract features. Initially, CNN is utilized to extract characteristics from 1D ECG patterns. The transformer then uses the CNN features and positional encoding as input to identify the ECG arrhythmia. CNN is utilized for local attention embedding in a 1D model, while the transformer's encoder is utilized for further feature extraction. In [23], the ECG signal feature is first retrieved via shallow-domain knowledge injection attention. The categorization in 2D After that, CNN receives multivariate inputs that include the smoothed ECG data and the attention outputs from the original. Additional research on CNN-transformer integration may be found at [32]. To detect ECG arrhythmia, 82 of the selected articles employ hybrid models, which combine several DL models.

f) DBN

CNN is widely used for classification, feature learning, and noise filtering. CNN classification frequently uses supervised learning.
The integrity may have been utilized to all feature branches by the global fully-connected Softmax layer. There were no hand-designed elements in the research, which adhered to the DL framework. Inter-patient variability, a major obstacle to automated diagnosis, was addressed by the patient-specific paradigm. The average accuracy of class-based MI localization and detection is 99.81% and 99.95%, respectively. The average accuracy of MI localization and detection in patient-specific tests was 94.82% and 98.79%, respectively [33].

g) GRU

GRU, an enhanced variant of LSTM, offers quicker training[34] . It uses less computer power and is easier to use than LSTM. To balance the information flow between units, GRU gates cooperate. The update gate is a novel gate made by combining the input and forget gates. The update gate restores equilibrium between the previous and candidate activations.

F. Medical Background

This section provides an overview of common cardiac illnesses that may be identified using ECG signals. ECG morphology represents the heart's condition. ECGs typically provide two sorts of information. A cardiologist can evaluate the time intervals on an ECG and determine how long an electrical wave takes to travel via the heart's conduction channel.[35]. This information identifies whether electrical activity is regular, erratic, rapid, or sluggish. A cardiologist can measure electrical activity to see if certain portions of the heart are overworked or excessively big. Three important components are among the numerous remarkable elements of a typical ECG heartbeat sample. An issue with the electrical activity of cardiac nerve cells that impacts ECG readings is called an arrhythmia. The most frequent kinds of arrhythmia are briefly outlined below:

a) Atrial Fibrillation (AF)
Atrial fibrillation (AF) is rapid firing of action potentials inside the atrium, resulting in a pace of 40-60 beats per minute. P waves are not visible because to the rapid atrial rate and low amplitude level[36].

b) Right and Left Bundle Branch Block
The Bundle Branch Block affects the usual conduction channel, causing an aberrant QRS form. An RBBB depolarizes the right ventricle instead of stimulating it by prolonging the impulse from the left bundle to the left ventricle (LV) and subsequently to the RV. This results in an uneven QRS shape. The left bundle frequently depolarizes the RV [37].

c) Premature Ventricular Contraction (PVC) and Premature Atrial Contraction (PAC)
PAC and PVC are caused by an early or premature heartbeat that throws off the heart's natural rhythm. PAC is the term for an early beat that starts in the atria. When it starts in the ventricles, it is referred to be PVC [38].

d) Ectopic beats

When an area outside the sinus node produces action potentials more quickly than the sinus node (atrial rate < 100 beats/minute), ectopic atrial rhythms result. Since the sinus node is not the source of the electrical activity, the P wave lacks the characteristic sinus appearance. Ectopic beats can happen when you're stressed or active, or after you've eaten something like alcohol [39].

e) Myocardial Infarction (MI)

When blood flow in a particular area of the heart slows or stops, it can result in MI, sometimes referred to as a heart attack, which damages the heart muscle or arteries over time[40]. Some MI patterns contain the two groupings listed below:

1. Patients with elevated ST segments or new RBBB/LBBB.
2. Individuals experiencing ST segment depression or T-wave inversion.

f) Fusion beat

Fusion beat is the term used to describe the simultaneous action of many electrical impulses on the same area of the heart. Currents clashing in the atrium result in Atrial Fusion Beats (AFB), whereas currents colliding in the ventricles result in Ventricular Fusion Beats (VFB) [41].

g) Idioventricular rhythm.

Idioventricular rhythm is comparable to VT since its ventricular rate is fewer than 60 beats per minute. The term "sluggish ventricular tachycardia" refers to the idioventricular rhythm [42].

h) Ventricular Bigeminy

Ventricular bigeminy is a cardiac rhythm disorder characterized by repetitive ectopic beats and numerous pauses between sinus pulses[43].

V. CONCLUSION

DL approaches for arrhythmia identification with ECG data have been intensively researched, and they have a high potential for use in clinical applications. However, as our data demonstrates, more investigation is required into certain essential elements of the DL pipeline before they can be employed with confidence in the categorization of clinical ECG arrhythmias. Future research opportunities and avenues that will ensure accurate DL-based arrhythmia classification and promote its application in real clinical settings include, in particular, using a variety of ECG databases for training and testing, developing advanced denoising and data augmentation techniques, developing new integrated DL models, and closely analyzing the inter-patient paradigm. The model employs both unsupervised and supervised training to automatically discover possible characteristics and interpolate missing information, which assists in the categorization of heart disease.

The advantages of CNN and VAE are combined in a novel hybrid architecture that facilitates the precise identification of cardiac anomalies in the ECG wave pattern. This is, as far as we are aware, the first time that 1-D ECG signals have been classified using VAE. The study's findings demonstrate efficient ECG signal categorization for a range of CVD types. When compared to the regular CNN and CNN-AE models, the suggested CNN-VAE model reduces mistakes and has a higher success rate. CNN-VAE's exceptional performance raises the possibility that it might be a useful tool for early CVD detection in medicine. The existing system may have a number of problems: The data imbalance needed to be addressed, and real-time data collecting might make this possible in the future. There are several potential issues with the current system: It was crucial to address the data imbalance, which may be done in the future by employing data augmentation techniques or by gathering real-time data samples. Model accuracy is significantly increased with a balanced dataset. Additionally, we are developing a mobile application (APP) that integrates the CNN-VAE model from this research.

This APP has the potential to be highly beneficial to medical practitioners since it can predict individuals who have high-risk cardiovascular disease. Given its exceptional efficacy, CNN-VAE may prove to be a useful medical diagnostic tool for the early detection of CVD. The existing system may have a number of problems: Resolving data imbalance was essential, and it may be accomplished in the future by using data augmentation techniques or gathering real-time data samples. Model accuracy is significantly increased with a balanced dataset. Additionally, we are developing a mobile application (APP) that integrates the CNN-VAE model from this research. The ability to forecast people with high-risk cardiovascular disease makes this APP potentially very helpful to medical professionals.

Examining the best Deep Learning algorithms for identifying various types of arrhythmia was the aim of the review technique. Technical specifics of popular techniques were discussed. The GRU/LSTM, CNN, and LSTM have demonstrated exceptional accuracy in reliably identifying atrial fibrillation, supraventricular ectopic beats, and ventricular ectopic beats, respectively. Furthermore, it is stated that adopting a suitable Deep Learning algorithm can significantly increase classification performance for the relevant application.

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