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Research Paper

Deep Learning Architecture for ECG Arrhythmia detection and classification: Recent Development, Challenges and Next Research Trend

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Abstracts: *The challenges of Electrocardiography (ECG) such interpretative discrepancies, resource-limited settings, power line interference and electrode contact issues which affect the accuracy of the recordings motivated the emergence of deep learning architectures. Deep learning algorithms, with their ability to extract and process large-scale datasets in ECG time series, have recently started gaining tremendous attentions. However, no comprehensive literature review exists on the applications of deep learning approaches to solve complex problems in ECG arrhythmia detection and classification. To fill this gap, we conducted a comprehensive literature survey on deep learning architectures in electrocardiography. The survey shows that application of deep learning algorithms in ECG arrhythmia detection and classification are increasingly becoming an interesting research area for solving complex problems. We introduce a new taxonomy of the domains of application of the deep learning architecture in ECG. The synthesis and analysis of the articles as well as their limitation are presented. A lot of challenges were identified in the literature and new future research directions to solve the identified challenges are presented. We believed that this article can serve as a reference guide to new researchers and an update for expert researchers to explore and develop more deep learning applications in ECG arrhythmia detection and classification.*

KEYWORDS: *electrocardiogram; ECG; deep learning; arrhythmia detection; cardiovascular disease.*

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I. INTRODUCTION

Over a period of years, the use of ECG has provided a good solution in the diagnosis and management of cardiovascular disease (CVD) such as heart arrhythmia. It benefits users for arrhythmia detection, prognostic prediction, technical quality assurance, quantify measurement and identify pathologic patterns. An ECG analyzes the heart's electrical activity and converts it into line tracings on paper called waves (Teich et al., 2000). An ECG scan depends on the placement of electrodes, which are small plastic patches that stick to the skin on certain spots on the patient's chest, arms, and legs. These electrodes record the electrical signals of the patient's heart and send them to a machine that maps the signals as waves for medical diagnosis. Given that arrhythmia is precipitated by malfunctions in the heart's electrical system, the ECG provides a directand non-invasive mechanism to examine these conditions (Sun et al., 2021).

Despite the benefits offered by ECG in detecting and classifying arrhythmia, the analysis of ECG faces several challenges. The requirement for physical contact points (electrodes) and their placement could affect the accuracy of the recordings while potentially causing discomfort to patients over extended periods. ECG signals are susceptible to noise and artifacts, such as powerline interference, muscle activity, electrode contact issues, and motion artifacts, distorting the waveform and affecting analysis accuracy. Additionally, the requirements of latency, low power and knowledge extraction from the large volume of physiological data are challenges. The problem relies in the possibility not to find most appropriate features which will give high classification accuracy in ECG problem. One way to obtain high accuracies is by using state-of-the-art analysis software typically those that employ deep learning and their variants trained on a large dataset.

Deep learning architectures have emerged to provide solutions to theaforementioned problems where it removes the need for manual feature selection and extraction, offering automatic feature selection and superior performance (Chandrasekar et al., 2023). Another advancement of deep learning has been to predict and classify healthcare data with extremely high accuracies (Oliver et al., 2018). As a result of that, deep learning algorithms have been applied in recent times to solve various problems such as object detection, anomaly detection, cyber security, fruit classification, street cleanliness, person re-identification, food recognition, smart vehicles and so on. Deep Learning can be introduced running on ECG. Also the application of deep learning architecture in ECG is attracting unprecedented attention from research community.

Despite the attention that the application of deep learning in ECG is attracting from research community, there is a lack of comprehensive systematic survey of the literature on the application of deep learning in ECG. In this regard, we conducted a comprehensive dedicated study on the applications of deep learning in ECG. The survey is in four perspectives: (1) technical perspective of the deep learning algorithms. (2), concise summary of EGG. (3) Technical view of the deep learning algorithms found to be applied in ECG. (4) Synthesis and analysis of the literature.

II. DEEP LEARNING

Deep learning has gained popularity because of advancement in computing capability by the advent of graphics processing unit (GPU), reduced hardware cost, and improved network connectivity (Zhao et al., 2019). Proliferation of training data and the current research progress in machine learning and information processing are also contributing factors to prominence of deep learning (Ahmad, Farman, & Jan, 2019). Deep learning uses a number (tens to even hundreds) of consecutive layers with each layer giving more significant representation of input data (Wani et al., 2020). Deep learning methods use artificial neural networks with multiple layers to learn hierarchical representations of data. They are instrumental in ECG analysis because they excel at extracting complicated features from raw input data. It has been applied in challenging fields of machine learning like image classification, voice recognition, handwriting transcription, natural language processing, self-driving cars and many more. Figure 1 presents the taxonomy of the deep learning architecture.

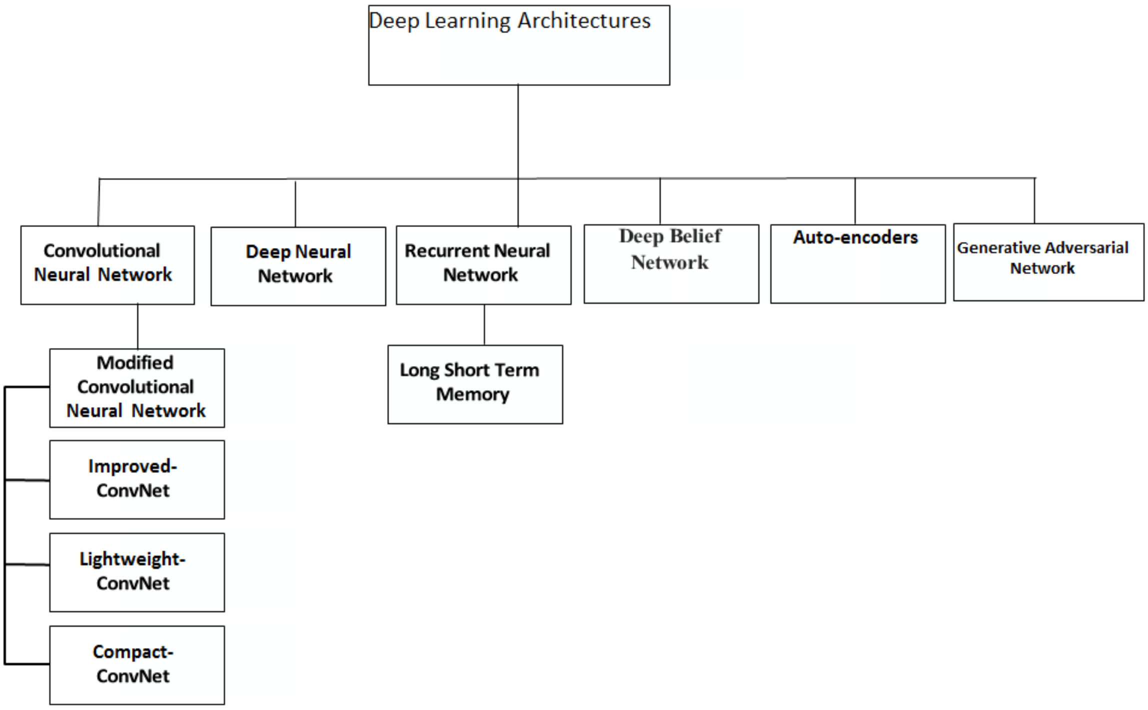

Figure 1: Taxonomy of Deep Learning Architectures

Many deep learning architectures exist in the literature. However, the scope of the study is the deep learning architectures used in solving problems in ECG arrhythmia detection and classification. The taxonomy is created based on the deep learning architectures that were found to be applied in solving problems in ECG arrhythmia detection and classification. The discussions on the different deep learning architectures are provided as follows:

2.1 Convolutional Neural Network

Convolutional neural network (CNN) is a deep learning algorithm primarily used for signal analysis, image recognition, pixel data, and natural language processing. They are fit at identifying spatial hierarchies or patterns using stacked trainable small filters called kernels (Hong et al., 2020). These kernels may effectively extract local information from the context of ECG data, such as the shape and duration of heartbeats, which are essential for diagnosing arrhythmias. Its strength was discovered to handle not only visual images but also many types of data with text and audio data. The ConvNet uses mathematical operation named convolution. It is a type of operation performed on two functions written as $(f * g)$ $where\ f\ and\ g$ are the functions. The convolution output for a given domain *n* is expressed as (Wani et al., 2020):

$$(f * g)(n) = \sum_{m} f(m)(n - m)$$

n is replaced by *t* when dealing with time-domain functions. The convolution equation can also be represented as:

$$(f * g)(n) = \sum_{m} f(n - m)(m)$$

Convolution can also be applied to multi-dimensional functions. For instance, given a two dimensional image as input denoted as Z, the 2D filter with size $m \times n$ denoted as K, 2D feature map denoted as X, the convolution operation can be expressed as;

$$\mathrm{X}(\mathrm{i},\mathrm{j}) = (Z * K)(\mathrm{i},\mathrm{j}) \sum_{m}\sum_{n} (m, n)K(\mathrm{i} - m, \mathrm{j} - n)$$

The operation is commutative and therefore can be written as:

$$\mathrm{X}(\mathrm{i},\mathrm{j}) = (Z * K)(\mathrm{i},\mathrm{j}) \sum_{m}\sum_{n} (\mathrm{i} - m, \mathrm{j} - n)(m, n)$$

The commutative property holds as a result of flipping the Kernel relative to the input. Without flipping the kernel, the convolution operation will be just as cross-correlation operation shown as:

$$\mathrm{X}(\mathrm{i},\mathrm{j}) = (Z * K)(\mathrm{i},\mathrm{j}) \sum_{m}\sum_{n} (\mathrm{i} + m, \mathrm{j} + n)(m, n)$$

The ConvNet has different types of layers performing varying tasks: convolution layer, activation function layer, pooling layer, fully connected layer and dropout layer. The convolution layer is the main building block for ConvNet. It uses convolution operation denoted as *. The layer majorly identifies features in the local region of a given image thatare recurrent in the dataset and maps their occurrence to feature map. It is normally stacked with activation function layer. For every filter in a layer, a feature map is obtained by repeatedly applying the filter over sub-regions of the whole image. The Convolution layer passes its output to activation function layer which in turn produces activation map as output using an activation function. Different activation functions exist. The most prominent is the Rectified Linear Unit (ReLU). Training is faster with ReLU. It is mathematically expressedas:

$$f(x) = \max(\mathrm{O}, x)$$

The Pooling layer decreases the size of the input. It receives feature maps from convolution layer and summarizes it by discarding unessential data while keeping discovered features. Feature extraction is done at the convolutional and pooling layers. The Fully connected layer is employed when there is need for classification. Each neuron from preceding layer has connection with every other neuron in the succeeding layer and each is significant in the classification decision. Finally, the last fully connected layer passes its output to a classifier, which in turn produces the class scores. The ConvNet performed better than almost all the prevalent methods in visual tasks. Different types of CovNet models have been proposed since its inception (Wani et al., 2020). The ConvNet architecture is presented in Figure 2.

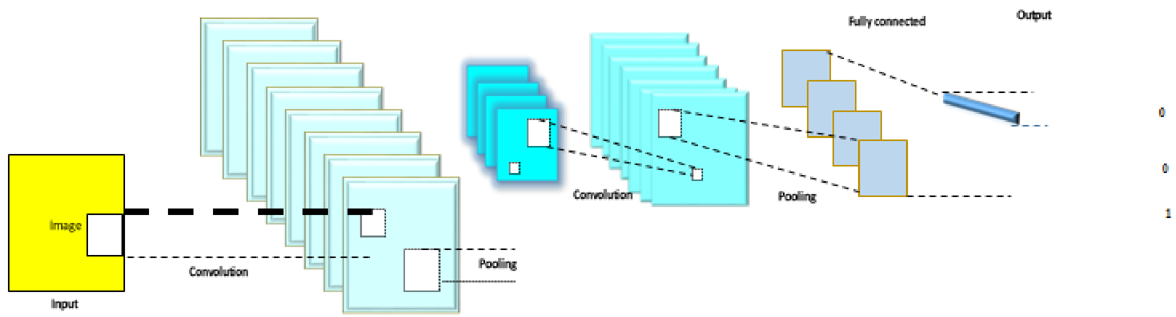

Figure 2: Convolutional Neural Network architecture

Deep ConvNet (D-ConvNet) can also be applied in regression task for mapping of input distance matrix to output distance matrix; pooling or dense layers are not involved in this case (S. P. Nguyen, Li, Xu, & Shang, 2017)

2.2 Deep Neural Network

Deep Neural Network (DNN) (Ciresan, Meier, Masci, & Schmidhuber, 2012) is a deep architecture mostly employed for solving regression and classification problems (Rav et al., 2017). It is in form of a hierarchy of layers with each layer containing some neurons. Succeeding layers progressively learn complex patterns from input received from preceding layers (Ahmad et al., 2019). The architecture of the DNN is shown in Figure 3. The DNNs are less complex structures due to the use of feed-forward networks with multiple layers.They perform well in handling non-sequential data.

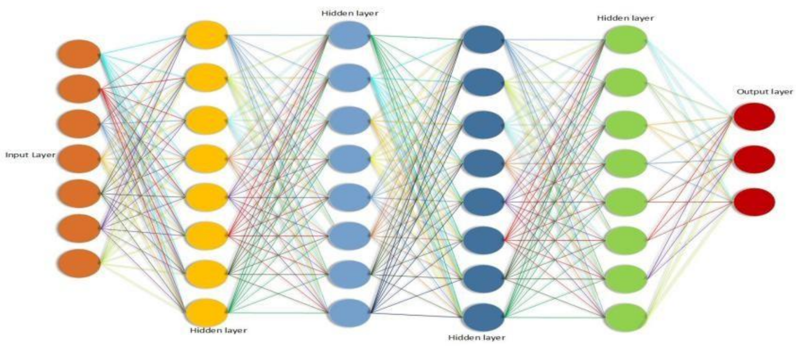

Figure 3: Architecture of the deep neural network

DNNs are trained with supervised and unsupervised learning techniques. The supervised learning methods utilize labeled data for training of the DNNs and error minimizing weights are learnt to accurately predict classification/regression target while the unsupervised learning methods do not need any labelled data to be trained and are mostly used in feature extraction, clustering, and or dimensionality reduction (Rav et al., 2017). Applications sometimes use the unsupervised learning in training the DNN to obtain most significant features at initial stage before applying the supervised learning for classification using those extracted features. In image classification for example, the DNN receives image as input, it generates vector scores for every class of objects, the class having the highest score is the most likely class of the image. Training is essential in DNN to obtain weights that maximize the score of thecorrect class and minimize scores of the incorrect class and the gap between the correctscores and the scores computed by the DNN is referred to as loss function (Sze, Chen,Yang, & Emer, 2017). In the training, weights are normally updated by gradient descent optimization process. To generally reduce the loss function, the weight vary iteratively by the following process (Sze et al., 2017):

$$W_{ij}^{t+1} = W_{ij}^{t} - (\partial L/\partial W_{ij})$$

Where W_{ij} denotes the weights, α signifies the learning rate.

A major weakness of DNN is its need for large dataset and powerful computing resources for iterative update of weights. Due to this, it is preferable to train the DNN at the cloud while inferencing can be done at the edge devices. Its application areas include healthcare, games, robotics, autonomous vehicles, etc.

2.3 Recurrent Neural Network

Recurrent Neural Network (RNN) (Elman, 1990) is a strong algorithm that is good in dealing with problems involving sequential input for example speech, video and text. RNN store temporal information and are exceptionally well suited for ECG analysis, where the sequential nature of cardiac rhythms is essential for spotting anomalies. This structure allows them to retain information across time, making them appropriate for ECG data processing (Khan and Kim, 2021). This implies that RNN harness the recent and past input to produce output for the newly received data. When given (x_1, $x_{2\ldots}$ x_r) as input sequence of vectors, RNN generates sequence of hidden states as (h_1, $h_2\ldots$, h_r) usually computed at a given time step t and expressed as:

$$h_t = \varphi W_h h_{t-1} + W_2 x_t$$

Where W_h signifies the recurrent weight matrix, W_x defines input-to-hidden weight matrix,and φ an activation function.

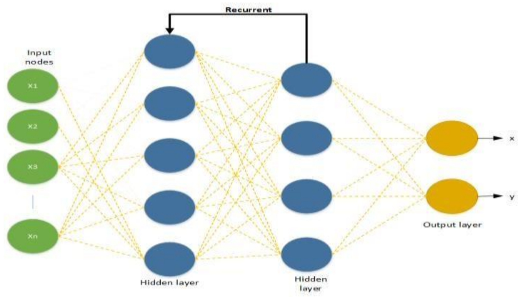

Figure 4: Architecture of the recurrent neural network

The deepness of RNN could be as far as the span of the input sequence (Deng, 2014). RNN can excellently predict next character or next word in a series. The RNNs mostly use sigmoid function as φ (activation function). But the algorithm is very difficult to train due an inherent problem known as "Vanishing gradient" (where back-propagated gradients vanish after multiple steps) (Deng, 2014). Architecture of the deep RNN is shown in Figure 4.

2.3.1 Long Short Term Memory

The long short term memory (LSTM) is a variant of RNN developed to provide solution to vanishing gradient problem associated with the RNN (Laurent et al., 2016). The LSTM has three layers; input layer, recurrent hidden layer, and output layer (Ma, Tao, Wang, Yu, & Wang, 2015). The architecture of LSTM consists of memory blocks where a memory block is formed by memory cells sharing common input gate and output gate which control the flow of error and weight conflicts in the memory cell (Hochreiter & Schmidhuber, 1997). A memory cell consists of a self-connected constant error carrousel (CEC), the CEC activation functions indicates the state of a cell. With the aid of the CEC, multiplicative gates (input and output gates) learn to open and close constant flow of error hence solving the issue ofvanishing gradient (Ma et al., 2015). Forget gate was incorporated in memory block to prevent limitless growth of internal cell values especially when dealing with incessant time series data that has been segmented earlier (Ma et al., 2015). This allows the memory blockto automatically reset when the information flow gets outdated and CEC weight is substituted with the forget gate activation.

Given an input sequence $x = (x_1, x_{2\ldots}\ x_r)$ and an output sequence $y = (y_1, y_2\ldots, y_r)$, LSTM iteratively performs computation expressed as: $t = 1\ to\ T$ (Sak, Senior, & Beaufays, 2014):

$$i_t = (W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i)\ f_t$$

$$= (W_f + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f)$$

$$c_t = f_t \circledS c_{t-1} + i_t \circledS (W_{cx}x_t + W_{cm}m_{t-1} + b_c)$$

$$o_t = (W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o)$$

$$m_t = o_t \circledS h\ (c_t)$$

$y_t = (W_{ym}m_t + b_y)$
With Ⓢ representing the scalar product of two vectors, and *W*s represent weight matrices, *b* represents bias vector, σ denotes sigmoid function, φ denotes the network output activation function, *i, f, o*, and *c* respectively denote input gate, forget gate, output gate and cell activation vector and *m* signifies the cell size. The LSTM has been successfully employed in different domains such as robotics, transportation, handwriting recognition, human actionrecognition, speech recognition, image translation, etc (Ahmad et al., 2019; Ma et al., 2015).

2.4 Deep Belief Network (DBN)

Deep Belief Network (DBN) (Hinton & Salakhutdinov, 2006) is a generative neural network with multiple layers. Each layer having visible units as its input and hidden units as its output. The layers but not the units are connected to each other i.e., the visible units are fully connected with the hidden units but no interconnection exists among visible units or between hidden units (Wani et al., 2020). DBNs are typically made up of stacks of Restricted Boltzmann Machines (RBMs) or auto-encoders, in which the hidden variables of each layer serve as the visible variables for the following layer. DBNs may help develop robust, discriminative models by discovering complex patterns inside datasets using the probabilistic model, which enables them to generate top-down models. They are, therefore, appropriate for applications requiring high-level data abstraction, such as identifying arrhythmia-indicating hidden patterns in ECG signals. DBNs may learn to represent ECG data in a way that captures the significant patterns or characteristics in the data, which assists in identifying irregular heartbeats and arrhythmias (Taji et al., 2017). The drawback of DBNs is that they, like other deep learning models, need a lot of labeled data for training, which can be difficult given the lack of labeled ECG datasets. DBNs are trained in an unsupervised way which gives it the strength to avoid over fitting and under fitting challenges (Wani et al., 2020). DBN generates a probability distribution expressed as (Good fellow et al., 2016)

$$P(h^{(l)}, h^{(l-1)}) \propto exp(b^{(l)T} + b^{(l-1)T} h^{(l-1)} + h^{(l-1)T} W^{(l)} h^{(l)})$$

$$P(h_i^{(k)} = 1 \mid h^{(k+1)}) = \sigma(b_i^{(k)} + W_{l,i}^{(k+1)T} h^{(k+1)}) \forall i, \forall k \in 1, \ldots, l-2$$

$$(v_i = 1 \mid h^{(1)}) = (^{(0)}_i + W_{l,i}^{(1)} h^{(1)}) \forall i$$

with $l + 1$ biasvectors as $^{(0)},..^{(l)}$ where $^{(0)}$ produces the bias for visible layer.

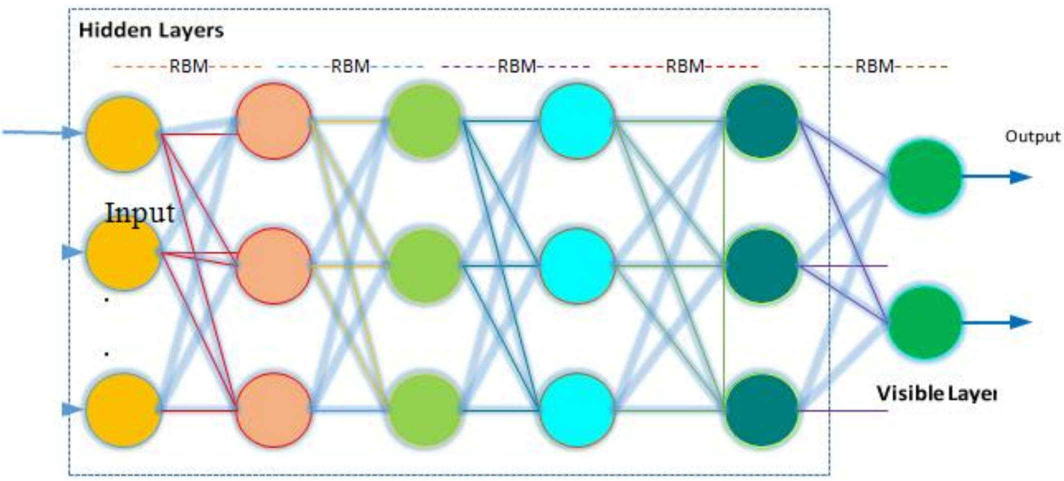

Figure 5: The architecture of Deep Belief Network.

Each layer of DBN is defined by a restricted Boltzmann machine (RBM). This implies the DBN if formed by a group of RBMs as depicted in Figure 7. The first layer of RBM can be trained with a given training data set as visible input. The output of the first layer serves as hidden unit to it and is sent to the next RBM to serve as visible unit for training. The process continues until the required RBMs are exhausted. The application of DBN has been seen in different domains, image processing is one of the example (Wani et al., 2020).

2.5 Autoencoders (AE)

An Auto encoder (AE) is an unsupervised DL approach originally proposed by (LeCun et al. 1998). It involves dimension reduction of the input dataand reconstruction of the input in the output layer (Shresthaand Mahmood 2019). An AE is a network of three layers; itbecomes a deep AE with multiple hidden layers. Both the input layer and output layer have the same number of units, represented with the same dimensionality and the hidden layers typically have fewer units that encodes the inputs in a more compressed form (Sengupta et al. 2020; Tobore et al. 2019). The AE architecture is presented in Fig. 12. Trainingof AE involves two phases: The encoder and the decoder. The network is trained using back propagation. During the encoding phase, the inputs are encoded into some hidden representations using the weight metrics of the lower half layer, and in the decoding phase, it tries to reconstruct the same input from the encoding representation using the metrics of the upper half layer. The encoding and decoding phases can be mathematically expressed as.

$$y^{?} = f\,(wx + b)$$

$$x^{?} = f\, w^{?} y^{?} + c$$

Where x and $x^{?}$ represents the input vector and reconstructed input vector in the output layer respectively. Variable w and b are the parameters to be turned, $w^{?}$ and c is the transpose of w, and the bias of the output layer respectively; y is the hidden representation and f is the activation function. The parameters are updated using the following Equations:

$$w_{new} = w - ??E/?w$$

$$b_{new} = b - ??E/?b$$

Where w_{new} and b_{new} stands for the updated parameters of w and b respectively and E is the reconstructed error of input at the output layer (Sengupta et al. 2020).

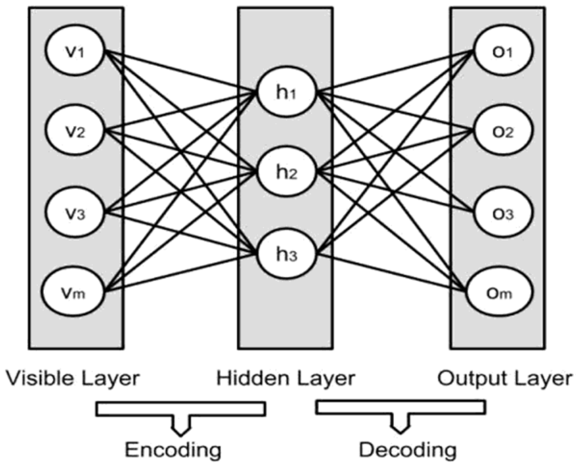

Fig. 6 Architecture of Auto-encoder (Sengupta et al. 2020)

2.6 Generative adversarial networks

Generative Adversarial Network (GAN) is DL architecture with unsupervised learning approach proposed by (Goodfellow et al. 2014). The GAN have two networks; generative and discriminator networks, that compete against each other in a zero sum gamesimultaneously (Alom et al. 2019). The generative model tries to capture the data distribution whereas the discriminative model learns to estimate the probability of a sample either coming from training data or the distribution capturedby the generative model. This can be viewed as a minmax two player game between these two models as the generative models produce adversarial examples while discriminative model trying to identify them correctly and both try to improve their efficiency until the adversarial examples are indistinguishable from the original ones (Sengupta et al.2020).

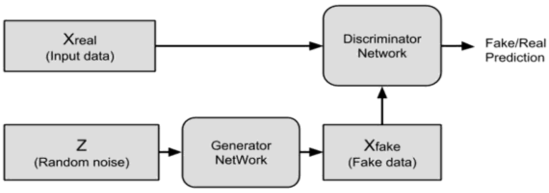

Fig. 7 Architecture of GAN

2.5 Comparing strength and limitations of the deep learning algorithms

The deep learning algorithms discussed in the preceding sections 2.1 to 2.6, each has its strengths, limitations and suitable application area. It is well known that no intelligent algorithm without a limitation despite the fact that those intelligent algorithms are powerful and effective in solving real world problems. In Table 1, the summary of the major strength, limitation and suitability of each deep learning algorithm discussed are presented.

Table 1: Summary of deep learning algorithms strength, limitations and suitability

Deep learning Algorithm	Suitability	Strength	Limitation
Convolutional Neural network	Image	Requires less neuron connections	Sometimes require many layers to extract hierarchy of features
Deep Reinforcement Learning	Decision making	Labeled data is not required	Tradeoff between Exploitation and Exploration Policy Evaluation and comparison is challenging
Recurrent Neural Network	Speech/Video	Memorizes sequential events Models time dependencies	Vanishing and exploding gradient Extremely difficult to train
Long Short TermMemory	Time series	Good for data with long time interval memory are secured by gate	Only handle short time dependencies High memory and bandwidth requirement
Deep Neural network	Regression	Dimension reduction	Learning process is sometimes slow it is computational intensive
Deep Belief Network	Computer Vision	Collaborative filtering	Training is more difficult as it challenging to calculate the energy function
Auto-Encoder	Image Compression	Noise removal	Inability to model the probalistic nature of data
Generative adversarial network	Text Classification	Image to Image translation	GAN can be notoriously difficult to train

III. ELECTROCARDIOGRAM (ECG)

Electrocardiogram (ECG) is one of the most commonly used tools for clinical evaluation of the heart due to its low-cost, simplicity and risk-free operation (Dilaveris et al. 1998; Elgendi, et al. 2014). An electrocardiogram is a form of a test that provides the measurementof electrical signals generated from the heartbeat activity. ECG is a non-invasive and non-expensive tool, efficient in diagnosing cardiac disorders such as arrhythmia, by continuous monitoring of the ECG. It records the electro physiological events in the heart, which is an indication of the electrical signal that is generated in the atria and ventricles through the process of depolarization and repolarization (Elgendi, et al 2014). The signals give information that can aid in analyzing and understanding the cardiac activity of a person such as heart rate, rhythm and morphology (Al Rahhal et al. 2016; Apandi et al. 2018; Park et al. 2019). Typically, the information provided by ECG test is the information of how long it takes for the electrical wave to pass through the heart by measuring time intervals on the ECG. This can help doctors todetermine if the electrical signal passing through the heartis normal or slow, fasts or irregular. Secondly, measuring the amount of electrical wave passing through the heart muscle would help a cardiologist to diagnose if a part of the heartis overworked or too large. Figure 8 shows the components of ECG wave forms recorded over an ECG machine. The P wave, the QRS complex and the T wave are the three main components of the ECG signal representing one cardiac cycle during a heartbeat (Hasan et al. 2012). Each wave form contains its interval and amplitude characterized by peaks and duration; this provides clinically useful information for cardiac arrhythmia detection (Thong et al. 2003; Tsipouras et al. 2002). The analysis of these waves is also critically useful for the detection of commonly known breathing disorders such as obstructive sleep apnea syndrome, as well as for studying the autonomic regulatory process of the cardiovascular system during sleep and/or hypertension (Trinder et al. 2001).

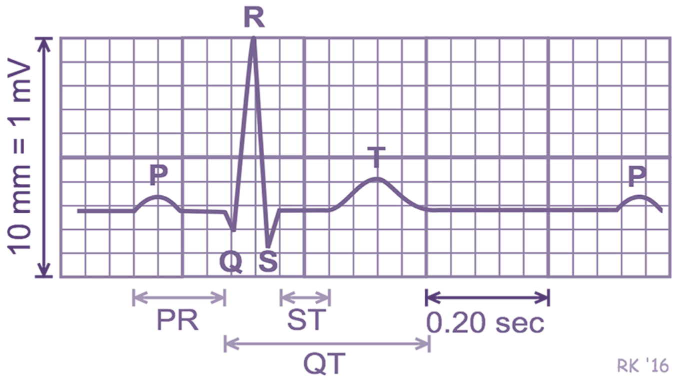

Figure 8: The ECG signal components

These waves give information about the electrical activities of the heart. The waves can be used for diagnosis of various heart disorders. The heartbeat is originated as an electric pulse from the sinoatrial (SA) node situated in the right atrium (singular of atria) of the heart. The SA node fires causing the atria to contract and pump blood to the lower chambers of the heart (ventricles). The depolarization process of the cardiac cycle is initiated by the firing of the sinoatrial node in the right atrium of the heart. The atria then depolarizes, causing the P wave to be produced. The P wave represents the normal atrial (upper heart chambers) depolarization, it shows how the electrical impulse (excitation) spreads across the two atriums of the heart. The Q, R and S waves that is called the QRS complex represents one single heartbeat and corresponds to the depolarization of the right and left ventricles (lower heart chambers). This occurs when the atria contract (squeeze), pumping blood into the ventricles, and then immediately relax. This is accompanied with the electrical pulse generated from the SA node which travels through the atrioventricular (AV) node that connects electrically the atria and the ventricles which activates the ventricles and cause the ventricles to contacts. The T wave represents the re-polarization (or recovery) of the ventricles. It shows that the electrical impulse has stopped spreading, and the ventricles relax once again (Antczak 2018; Banerjee et al. 2019; Swapna et al. 2018).

IV. DEEP LEARNING ALGORITHMS IN ELECTROCARDIOGRAM (ECG)

In this section, we present different projects where researchers applied deep learning algorithms to solve problem in Electrocardiogram (ECG). Figure 9 is the taxonomy of the application of deep learning in Electrocardiogram (ECG). The taxonomy indicates the deep learning algorithm in the relevant ECG.

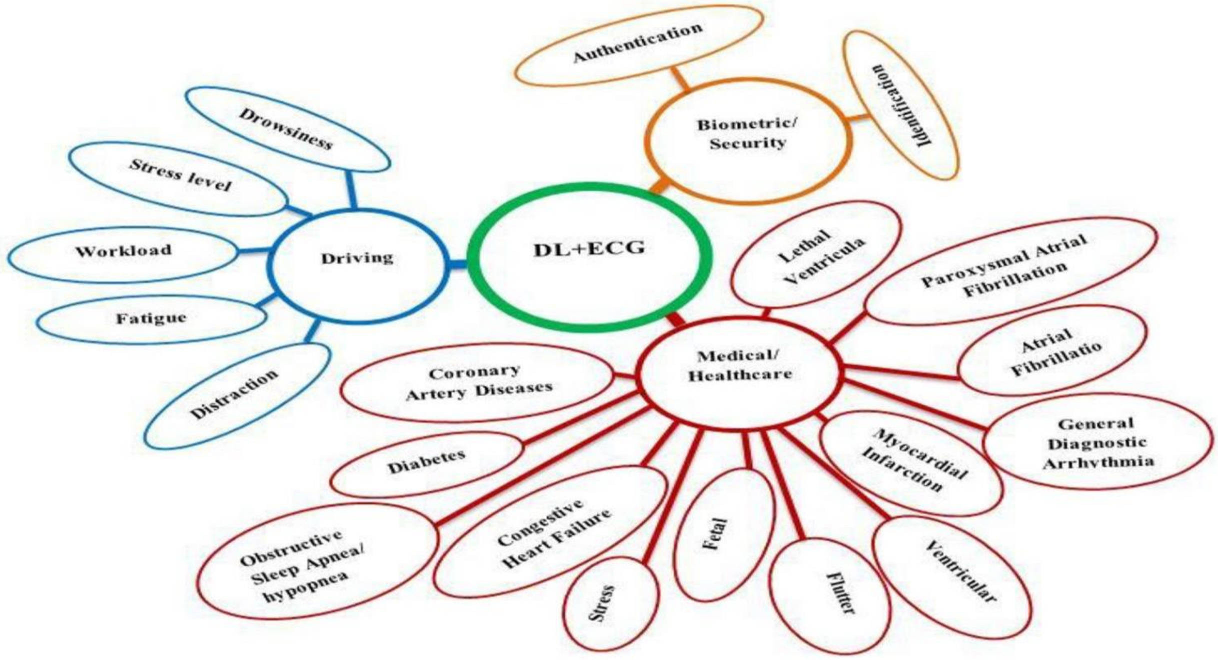

Figure 9: Taxonomy of the application of deep learning in Electrocardiogram

4.1 Convolutional Neural Network

Many projects applied ConvNet in ECG to solve different categories of problems. The summary of the applications of ConvNet in ECG is presented in Table 2. The discussions of the applications of ConvNet in different ECG are presented as follows:

4.1.1 Convolutional Neural Network in ECG

The applications of ConvNet in ECG to solve problems is presented in this section, for example, A study by (Acharya et al. 2017) proposed a CNN model for automatic detection of MI. The study demonstrated the effect of noise by removing baseline wander in the ECG signals in the first pump blood to the dataset and kept the noise on the other dataset. The result shows that the performance recorded were 93.53%, 93.71% and 92.83% for accuracy, sensitivity and specificity, respectively (using dataset with noise). The de-noised dataset obtained better performance with accuracy of 95.22%, sensitivity of 95.49% and specificity of 94.19%, all evaluated on the PTBDB.

AF detection was studied by (Xiong et al. 2017) using CNN model. The result of the CNN is compared with the RNN and spectrogram learning. The proposed CNN model outperformed the compared algorithms with 82% over all accuracies. However, imbalance ECG data and varying lengths affected the performance of the model. There are health challenges associated with sleep disorder which have been investigated. Among which include obstructive sleep apnoea (OSA) or sleep apnoea syndrome (SAS). Polysomnography (PSG) is the standard methodfor sleep apnoea diagnosis. However, because of the cost and time consumption involved in the PSG, recently, studies move toward effective classification of sleep apnoea based on ECG signals.

A studyby (Zhang et al. 2017) proposed a 2D-CNN model for human identification. The study used Single-arm-ECG signal data acquired from 10 subjects and achieved IR of 98.4%.

A study by (Pyakillya et al. 2017) proposed a 1D-CNN model for ECG signal classification task. The study was evaluated on the PhysioNet/ Computing in Cardiology Challenge 2017 (PhysioNet/CinC2017) dataset and obtained an accuracy of 86%. The CNN model, however, imbalance dataset is used. The authors proposed to use GANs to solve the imbalance dataset problem.

A study by (Acharya, Fujita, Lih, Hagiwara, et al., 2017) proposed a CNN model to detect different arrhythmias. The study proposed two CNN architectures (Net A and Net B) with 500 input and 1250 input samples respectively. The performance of the two proposed CNNs in terms of accuracy, specificity and sensitivity is greater than 90% respectively with exception of Net B that achieved 81.44% accuracy using the Creighton University Ventricular Tachyarrhythmia database (CUDB), MIT-BIH atrial fibrillation database (AFDB) and MIT-BIH arrhythmia database (MITDB). The DL architectures demonstrated good performances with 2 and 5 s ECG segments respectively. However, there was limited data for training and too much training time was observed. Data augmentation and bagging algorithm could solve limited data problem.

A study conducted by (Li et al. 2017) proposed a novel approach by fusing the morphology and rhythm of heartbeats to feed into a CNN model for ECG classification. The authors used one-hot encoding technique to convert the 1D ECG signals to 2D images to improve the convergence speed and improve the accuracy. The model was tested on the MITDB and achieved a performance of more than 90% accuracy on both SVEB and VEB. However, the specificity and accuracy of V beat was lower than the compared methods because of the use of raw ECGwithout representation extraction.

A study by (Xia et al. 2017)proposed a CNN model in an end-to-end classification of AF. The model received an input from the transformed ECG segments by STFT and stationary wave let transform (SWT) respectively. The models were evaluated on the AFDB and achieved competitive performance with sensitivity of 98.34%, specificity of 98.24% and accuracy of 98.29% (STFT-CNN). On the other hand, SWT-CNN model achieved sensitivity of 98.79%, specificity of 97.87% and accuracy of 98.63%.

Amrani et al. 2018 proposed a very deep CNN model as feature extractor using a fusion technique called multi-canonical correlation analysis (MCCA), and the extracted features were classified using Q-Gaussian multi-class SVM (QG-MSVM). The effect of the fusion technique was observed to outperform the compared methods with 97.37% accuracy for arrhythmias detection analysis. The fusion technique may introduce additional training time.

A Deep residual CNN model was proposed by (Kachuee etal. 2018) for Arrhythmia classification. The model was used for myocardial infarction (MI) prediction. The performance achieved was 93.4% accuracy for arrhythmia classification,and 95.9% accuracy for MI prediction on the PTBDB.

Sleep apnoea classification based on CNN model was proposed by (Dey et al. 2018). Using the apnoea-ECG dataset from Physionet, the model achieved an accuracy of 98.91%. However, mostly expert observation is done in offline process

A Multi-Scale CNN (MCNN) was proposed by (Z. Yao & Chen, 2018). Although the study used single lead ECG as input without considering rhythm information, the model achieved performance better than the methods that use hand-crafted features with 88.66% overall accuracy on SVEB and VEB. Landmark information can be utilized to improve performance of the model.

In another study, (Q. Zhang & Zhou, 2018) proposed 2D-CNN model for human identification. The model was tested on dataset acquired from single-arm-ECG and ear-ECG. Result shows it achieved IR of 98.4% and 91.1%, respectively. However, the ECG signals acquired from these studies were weak.

A study by (Deshmane & Madhe, 2018) proposed 1D-CNN model for human identification and tested the model over four databases. The performance accuracies of 81.33% (MITDB), 96.95% (Fantasia database), 94.73% (NSRDB) and 92.85% (QT database) were obtained

A study for in attention identification was presented by (Taherisadr et al., 2018) to provide an early distraction detection system that could help prevent accidents on the roads while driving. They first extracted Mel frequency spectral coefficients (MFSC) representation of raw ECG signals and fed the 2D spectrogram images into the proposed deep CNN and achieved accuracy of about 95.51% which was better than using time frequency (TF) representation. The model was tested with ECG signals acquired from naturalistic setting driving of 10persons. The limited population used can be increased to getmore data to train the model.

A study by (Diker and Engin 2019) proposed a model combining CNN and Extreme Learning Machine (ELM) for classification of ECG signals. Although the performance accuracy was below 90% (88.33%) using Physikalisch-Technische Bundesanstalt Diagnostic database (PTBDB), yet was found to be better compared with the traditional models such as K-NN, Decision Tress and SVM.

Hao et al. 2019 for ECG beats classification. The authors used beat-to-beat and single-beat information. At first, it converted ECG signals using short-time Fourier transform (STFT) and wavelet transform to obtain spectrotemporal images that were fed into the model for training. The model obtained a comparable detection performance based on sensitivity and positive predictive value(PPV).

Huang et al. 2019 proposed 2D-CNN model which was used to train ECG images transformed using STFT. The model was simulated on the MITDB and obtained accuracy of 99.00% for ECG classification task over the ID-CNN.

A CNN model was proposed by (Kaouter etal. 2019) for ECG classification task. The model was compared with Ensemble of Fine-Tuned CNN, VGG Net-16 and Res Net-50 and CNN full training, Google Net-144 layers was found to produce the best performance accuracy with 93.75% using ECG signals evaluated on the MITDB, MIT- BIH normal sinus rhythm database (NSRDB) and Beth Israel Deaconess Medical Center (BIDMC) congestive heart failure database. However, the diagnostic value of the proposed model can be improved by including other parameters of patients other than the ECG signals.

In a study by (Pandey and Janghel 2019), it proposed a CNN-based model for arrhythmia detection problem. Because of the imbalance in the MITDB, Synthetic minority oversampling technique (SMOTE) technique was used to solve the imbalance problem. The model achieved a good performance with 98.30% accuracy, 86.06% precision, 95.51% recall and89.87% F1-score.

Another study by (Acharya et al. 2019) proposed a CNN model for the diagnosis of CHF. The study evaluated the model based on the combination of databases into set A, B, C and D. Set A (NSRDB, BIDMC), Set B (Fantasia, BIDMC), Set C (NSRDB, BIDMC) and Set D (Fantasia, BIDMC). The CNN model achieved accuracy, sensitivity and specificity greater than 90% in each of the scenarios.

A study by (Ahmed et al. 2019) proposed a CNN model to predict MID, however, the authors optimized the CNN model using Ant Colony Optimization (CNN-ACO). An accuracy of 95.78% was recorded on the UCI-ML Repository. The CNN-ACO model, however, consumed a lot of memory compared with the basic CNN model, likely because of the additional ACO.

The automatic detection of MI was proposed by (Alghamdi et al. 2019) using a pre-trained deep CNN (VGG-Net). Two architectures of VGG-Net (Fine-tuning and VGG-Net as fixed feature extractor) were proposed, namely, VGG-MI1 and VGG-MI2. The VGG-MI1 is based on the VGG-Net model with little fine-tuning. And VGG-MI2 was used as the feature extractor and QG-MSVM as the classifier. It improves the accuracy by 2%. VGG-MI2 obtained the best accuracy of 99.22% on the PTBDB.

A study proposed by (Baloglu et al. 2019) used deep CNN model to classify MI. Result indicated that the accuracy of 99.78% was achieved on PTBDB. However, the model did not detect the locations of the MI.

A 2D-CNN model was proposed for human identification (Abdeldayem & Bourlai, 2019). The model was tested on eight different databases and obtained the best average identification rate (IR) of 95.6% on the combined databases. However, the study suggested employing multi-session scenario to improve the model performance.

A study presented by (Ranjan, 2019) for user authentication investigated the permanence of the biometric and the impact on system accuracy on day-to-day variations in ECG. The system achieved EER of 2.0% (minimum EER of 0.9%) tested on PTBDB. However, the authors observed that the accuracy degrades due to single session enrollment as days pass by.

In another study by (Hammad & Wang, 2019) a pre-trained CNN based model was built, VGG-Net was used for feature extraction combined with QG-MSVM for authentication in a parallel score fusion of ECG and fingerprint. The model was tested on PTBDB and LivDet 2015 database and accuracy of 99.99% was achieved.

In another study, Pilot workload prediction was proposed (Xi et al., 2019). Two visual representations: spectrograms and scalograms were used on the acquired ECG. And a pre-trained CNN model, AlexNet was used as "off-the-shelf" feature extractor and the well- known linear classifier, SVM was used for the prediction. Compared with the fine tuning Deep CNN, AlexNet + SVM achieved the best performance with accuracy of 51.35% (scalograms + AlexNet-SVM). However, the dataset was collected from 2 qualified test pilots performing a target tracking task on the National Research Council of Canada's (NRC) Bell 205 helicopter which is very limited for a real setting.

A study conducted by (Dokur and Ölmez 2020) proposed a heartbeat classification model based on CNN, excluding the fully connected neural network (FCNN) part of the basic CNN model. However, a Walsh functions was applied to maintain performances during training. Also, the drawback of converting one-dimensional (1D) ECG signals to two-dimensional (2D) images was investigated. The average accuracy of 99.45% and 98.7% for 1D ECG signals and 2D ECG images, respectively, were achieved when evaluated using the MITDB.

A recent study conducted by (Ribeiro et al. 2020) proposed a residual framework (ResNet), for effective diagnosis of ECG using 2, 322, 513 ECG records of private dataset collected from 1,676,384 different patients. Using the short-duration and standard 12-lead ECG, the model achieved F1-score greater than 80% and specificity greater than 99%.

The ECG classification task using deep CNN and two-stage deep CNN was proposed by Shaker et al. (Shaker et al. 2020). The authors also demonstrated the effectiveness of heartbeat augmentation using GANs which yielded better performances compared with the unbalanced data. The models achieved overall accuracy > 98.0%, precision > 90.0%, specificity > 97.4% and sensitivity > 97.7%. However, post-processing method such as smoothing filter can be applied to enhance heartbeat quality. Also, outlier removal can enhance precision results.

CNN-based architecture was utilized for feature extraction in a study proposed by (Zhou and Tan 2020). The authors used extreme learning machine (ELM) for the classification of the ECG and achieved 98.77% accuracy on the MITDB.

An Ensemble of Exception, ResNet, and Dense Net model were proposed (Byeon et al., 2020). The authors used spectrogram, melspectrogram, log-spectrogram, scalogram and MFCC to obtain time-frequency representations that were fed into the pre-trained CNNs models. Experiments result showed that the best accuracy of ensemble by time frequency representation was Exception with 99.05% using average of scores from log spectrogram to spectrogram. Also, the best accuracy of ensemble by opened CNN model was MFCC with 99.04% using average of scores from Exception to Dense Net.

A parallel ensemble CNN model was proposed by (Kim et al. 2020) for user recognition. The authors proposed this model to deviate from the problem of over fitting when data obtained from different sources changes the user state is presented as registered data, which may lead to data generalization. Consequently, degrade the recognition performance of newly data. Therefore, the various ECG signals acquired from different states were passed into the ensemble networks and the output was fused into one database for re-training. The model achieved performance accuracy of 98.5%. However, the ECG signal was collected using only one device; this may affect the model's generalizability.

A novel study was proposed by (Y. Li, Pang, Wang, & Li, 2020). They proposed a CNN-based model called Cascaded CNN (F-CNN + M-CNN). The F-CNN model was used as feature extractor and M-CNN was used for the identification task. Both the two trained models were cascaded to form the cascaded CNN for final identification. The model performance is found to be better than the existing approaches with accuracy of 94.3% (3s, 18–40 subjects) and 97.1% (7s with 5 datasets). However, the model still suffers from intra-subject variability.

Two CNN models were proposed by (Hammad et al. 2020) for human authentication. The first model was a 1D-CNN and the second was a pre-trained model (ResNet) with attention mechanism called ResNet-Attention. The proposed ResNet- Attention model achieved better performance with accuracy of 98.85% and 99.27% on PTB and CYBHi, respectively. However, ECG template protection was not used.

A recent study by (Peimankar and Puthusserypady), 2021 proposed DL models that eliminate the feature engineering step and extend ECG classification to more classes, they also echo the recurring theme of ECG waveform delineation challenges and the necessity of a more extensive and more diverse dataset. A good accuracy of 99.56%, sensitivity of 97.01% was obtained based on evaluation on the QT DB. However, their method relied on a small database for training and testing.

A recent study by (Midani et al., 2023) suggests a novel methodological approach that combines feed-forward and recurrent deep neural networks using a sequential fusion method. This approach aims to better represent relevant features of arrhythmia in ECG signals. A good accuracy of 99.436%, sensitivity of 97.01% and specificity of 99.57% were obtained based on evaluation on the MIT-BIH. However, their method relied on a small database for training and testing and used R peak segmentation based on dataset annotation.

Table 2: Summary of the Convolutional Neural Network applications in ECG

Reference	Deep learning structure	Application	Data	Accuracy	Limitation
(Acharya et al. 2017)	CNN	Automated Detection of MI	PTBDB (200 subjects)	Acc = 93.53% Sen = 93.71% Spe = 92.83% (with noise), Acc = 95.22% Sen = 95.49% Spe = 94.19% (without noise)	• Takes too much time during training. • Requires huge data.
(Xiong et al. 2017)	CNN, RNN, Spectrogram +GoogleNet	Detection of AF	Physionet/CinC Challenge 2017 (8,528 records)	F1 scores: 0.82 (CNN), 0.72(RNN)	• Limited dataset for training. • Imbalance ECG data problem and varying signal lengths. • Propose data augmentation to solve class imbalance andproblem.
(Zhang et al. 2017)	2D-CNN	Human identification	SADB (10 subjects)	ID rate = 98.4%	• Require large data set for training to improveperformance. • The acquired data werenoisier and weaker than the standard chest-ECG.
(Pyakillya et al. 2017)	ID-CNN	ECG Classification	PhysioNet/CinC Challenge 2017 (Not stated)	Acc = 86%	• Imbalance data problem, this can be solved using GAN networks. • Unsatisfied comparison to other DL solutions in terms of computational complexity, proposed architecture andoptimization methods.
(Hagiwara, et al., 2017)	CNN	Detection of arrhythmias	CUDB, AFDB, MITDB (21,709 segments of 2s	Net A: Acc = 92.50% Sen = 98.09% Spe = 93.13% Net B: Acc	• Require more data fortraining • Long convergence

			(Net A), 8683 segmentsof 5s (Net B)	=94.90% Sen =99.13% Spe = 81.44%	time • Data augmentation and bagging algorithm should be considered
(Li et al. 2017)	ID-CNN	Classification of ECG	MITDB (48 records)	Acc =97.5%	• Takes a lot of training time • It will require new trainingwhen the model is changed • More leads should be investigated
(Xia et al. 2018)	STFT-DCNN, SWT-DCNN	Detecting AF	AFDB (23 records)	STFT-DCNN Sen= 98.34%,Spe = 98.24%Acc = 98.29% SWT-DCNN: Sen = 98.79%, Spe =97.87% Acc =98.63%	• Small number of datasetswas used
(Amrani et al. 2018)	Very deep CNN and MCCA Fusion + QG-MSVM, Very deep CNN without Fusion QG-MSVM	Arrhythmias detection	MITDB, AFDB, SVDB (111,901 ECG segments)	Acc = 94.74% (without fusion techniques) Acc =97.37% (applying MCCA)	• The fusion technique may increase computational time
(Kachuee et al. 2018)	Deep residual CNN	Heartbeat / MI classification	MITDB (47 subjects), PTBDB (290 subjects)	Heartbeat classification: Acc =93.4% MI classification (PTBDB): Acc: 95.9% Precision: 95.2% Recall: 95.1%	• Require more data for training to improve performance
(Dey et al. 2018)	CNN	Obstructive sleep apnoea (OSA) detection	Apnoea-ECG dataset from Physionet (35subjects)	Acc: 98.91%, Sen: 97.82%, Spe: 99.20%	• Takes too much time duringtraining • Mostly expert observation is an off-line process • The model can be applied onEEG, EOG, EMG for same purpose
(Z. Yao & Chen, 2018)	MCNN	Arrhythmia Classification	MITDB (48 records), private dataset HEDB (22 records)	Over all Acc = 0.8866, Acc = 0.9600 (SVEB) Acc =0.9250 (VEB)	• Propose to use land mark information of rhythm to improve performance
(Deshmane and Madhe 2018)	1D-CNN	Human Identification	MITDB, Fantasia database, NSRDB and QT (210 subjects	Acc = 81.33% (MITDB), 96.95% (Fantasia database), 94.73% (NSRDB), 92.85% (QT)	• Need for more dataset for training and testing model
(Taherisadr et al. 2018)	MFSC + DCNN, TF+DCNN	Driver in attention identification	Naturalistic setting where subjects drove a real car (Ford Escape 2015) (10 subjects)	Acc around 95.51%	• Small population is used in the study
(Diker and Engin 2019)	CNN+ELM	Classificationof ECG signal	PTBDB (294 subjects)	Acc= 88.33%, Sen = 89.47% Sp = 87.80%	• DL architectures will be investigated for classification to improve performance
(Hao et al. 2019)	WT and STFT + Multi-channel dense CNNs	ECG beat classification	Dataset from Biofourmis for training (more than 10,000 ECG records), MITDB for testing (44 subjects)	Sen = N (97.0) L (98.9) R(91.4) V (95.0) S (90.4)PPV= N (97.7) L (92.2) R(90.2) V (94.5) S (91.5)	• Limited dataset was used
(Pandey and Janghel 2019)	CNN +	Detection of arrhythmia	MITDB (47 subjects)	Acc = 98.30% Pre =	• Larger dataset is required fortraining to improve

	SMOTE			86.06% Recall: 95.51% FI-Score = 89.87%	generalization ability • Require implementationusing real dataset
(Kaouter et al. 2019)	CNN	ECG signals classification	MITDB (47 subjects), NSRDB (18 subjects), BIDMC congestive heart failure database (15 subjects)	Acc = 93.75%	• Require more data for training model • Other parameters of patientsother than ECG signals can improve the diagnostic value of the proposed model
(Acharya et al. 2019)	CNN	Diagnosis of CHF	BIDMC Congestive Heart Failure Database, Fantasia Database, NSRDB (73 subjects)	Set A (NSRDB, BIDMC): Acc = 95.98%, Sen = 96.52%, Spec = 95.75% Set B (Fantasia, BIDMC): Acc = 98.97%, Sen =98.87%, Spec = 99.01% Set C (NSRDB, BIDMC): Acc = 94.40%, Sen = 94.68%, Spec = 94.12% Set D (Fantasia, BIDMC):Acc = 98.33%, Sen – 98.50%, Spec = 98.16%	• Takes too much time duringtraining • Require huge data for training
(Abdeldayem and Bourlai 2019)	2D-CNN	Human identification	CESBDB, NSRDB, Fantasia, MITDB,STDB, AFDB, VFDB, PTBDB, Combined (388 subjects)	Average IR = 95.6% FAR = 0.2% FRR = 0.1%	• Multi-session scenarioshould be considered • Removal of ECG abnormalities stage should be integrated
(Hammad and Wang 2019)	VGG-Net + QG-MSVM	Human authentication	PTBDB (290 subjects), LivDet2015 Database (200 subjects)	Acc = 96.56% FAR = 0.033% FRR = 0% (PTBDB) Acc = 98.48% (LivDet2015) performance (based on ECG and fingerprint) EER = 0.01% (based on different biometrics) Acc = 99.99%	• Different level of fusion was suggested • Reducing the biometricfeatures size to speed up authentication is suggested • Proposed testing themodel on real data
(Ranjan et al. 2019)	CNN	User authentication	Private dataset of 400users (train) and ECG-ID database (89 subjects)	EER = 2:0% (minimum EER = 0:9%)	As days pass by the accuracy degrades due to singlesession enrollment
(Xi et al.2019)	AlexNet + SVM	Pilot Workload Prediction	Data collected using qualified test pilots performing a targettracking task on the NRC Bell 205 helicopter (2 subjects)	Acc 51:35% (scalograms +AlexNet SVM)	• Vary small populationfor testing • There isneed to improve performance
(Ahmed et al. 2019)	CNN-ACO	Prediction of MI	UCI-ML Repository (43,401 people's records)	accuracy = 95.78%	• Consumes memory • Map Reduce to reduce memory consumption
(Baloglu et al. 2019)	Deep CNN	Classificationof MI	PTBDB (200 subjects)	Acc = 99.78%, Sen = 99.80%	• Time computational cost • MI location in ECG signalswas not considered
(Dokur and Ölmez 2020)	CNN without FCNN	Heartbeat classification	MITDB (47 subjects)	Acc = 99.45% (ID ECG signals),98.7% (2D ECG images)	• Limited to detect arr ythmis • Proposed model can be deployed on mobile phones
(Ribeiro et al. 2020)	ResNet	Diagnosis of the ECG	Private dataset having 2,322,513	F1- score > 80%Spe > 99%	• It was not convincing that the proposed

			ECG records from 1,676,384 different patients of 811 counties in the state of Minas Gerais/ Brazil from the TNMG		model is better than the medical residents and students with statistical significance on McNemar statistical test and bootstrapping • The proposed model can be applied for myocardial infarction, cardiac chamberenlargement
(Shaker et al. 2020)	Deep-CNN and Two-stage deep-CNN	ECG classification	MITDB (48 records)	Acc > 98.0%, Pre > 90.0%, Spe > 97.4%, Sen > 97.7%	• Need to apply post-processing using smoothing filter to enhance the quality of heartbeats • Outlier removal should be applied to enhance precisionresults • Other variant of GAN shouldbe investigated with different deep network architectures
(Byeon et al. 2020)	Emsemble of Xception, ResNet, and DenseNet	Individual identification	PTBDB (290 subjects)	The best acc of ensemble by time frequency representationis Xception of 99.05% using average of scores from log spectrogramto spectrogram. The best acc of ensemble by opened CNN model = MFCC of 99.04% using average of scores from Xception to DenseNet	• More robust ensemble methods will be studied
(M.-G. Kim et al.2020)	Parallel ensemble CNN	User Recogni tion	MITDB (47 subjects) and acquired ECG signals for 89 adults under different states	Acc = 98.5%	• Small population wasused • Only one device wasused to acquire ECG signals • Wearable devices shouldbe used to acquire ECG data for real application
(Y. Li et al. 2020)	(F-CNN + M CNN)	Human identification	FANTASIA (40 subjects), CEB-SDB (20 subjects), NSRDB (18 subjects), STDB (28subjects), AFDB(23 subjects)	Acc = 94.3% (3s, 18-40subjects), 97.1% (7s with the 5 datasets)	• Intra-subject factors problem • Proposed to capture more robust characteristics by eliminating theeffect of different statesshould be investigated
(Hammad et al. 2020)	ID-CNN, Res Net attention	Human authentication	PTBDB (290 subjects), CYBHi data-base (65 subjects)	**ResNet-Attention**: Acc = 98.85%. EER:139%(PTB), 99.27% EER: 0.68%. (CYBHi) **1D-CNN**: Acc = 98.59%. EER: 1.53% (PTB), 99.72% EER: 0.27% (CYBHi)	• Small dataset was used • ECG template protection method was not used • Propose deploying themodel on cloud using IoTs
Peimankar and Puthusserypady (2021)	CNN-LSTM	ECG classification	QT DB (4 subject)	Acc = 99.56%	• Limited dataset was used
(Midani et al., 2023)	CNN + BiLSTM	Detection of arrhythmia	MIT-BIH(5 subject)	Acc = Acc = 99.46%, sen = 97.01%, spe = 99.57%	• Limited dataset was used

V. DEEP NEURAL NETWORK

In this section, we present different DNN proposed by different researchers in solving problems in ECG. Table 3 present the summary of theDNN application.

5.1.1 Deep neural network in ECG

The applications of DNN in ECG are presented in this section. The work of (Xu et al. 2017) proposed Arrhythmia classification based on DNN model. The study investigated the effect of preprocessing methods. A method called Fisher discriminant ratio (FDR) produced the best performance with accuracy of 82.96% evaluated using UCI cardiac arrhythmia dataset. However, there was limited data and unbalanced data problem.

A DL network was proposed by (Chamatidis et al. 2017) for human authentication. The model first converted the ECG signals using three transformations: Discrete Cosine Transform (DCT), Fourier Transform (FT), and Discrete Wavelet Transform (WT) and then fed into theDNN for authentication. However, the model performed poorly compared with the KNN classifier, MLP classifier, Radial basis function network (RBFN) classifier and Random Forest classifier, largely due to insufficient data for training. The authors proposed to incorporate cancelable mechanism to protect the system against security attacks

Arrhythmias detection using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) as features extractors from ECG signals and performed classification using DL was proposed in (Assodiky et al., 2017). Using 452 data samples from UCI-ML Repository, model performance was indicated that PSO have the highest accuracy of 76.51%. It was also shown that PSO reduces features of 261 to 23 attributes whereas GA reduced to 31 attributes. Although, the number of normal ECG signals classes were higher than theother classes.

A DNN model was proposed by (Wieclaw et al. 2017) for human identification. The study was evaluated on Lviv Biometric Data Set which contains 18 subjects' recordings and produced accuracy of 88.97%. However, distortion of ECG signals and limited data affected the performance. Data augmentation based on GANs can be employed.

In a study conducted by Xu (S. S. Xu, Mak, & Cheung, 2018) an end-to-end DNN model to classify ECG beats was proposed. The study evaluated their model based on expert intervention and without expert intervention. The results show that a better result without expert intervention on S and V class of ECG beats evaluatedon the MITDB was achieved. However, there was limited data and imbalance data problem.

In a study by (Sannino & De Pietro, 2018), the authors proposed a DNN model that utilized temporal feature extraction and classified ECG signals. A goodaccuracy of 99.68%, sensitivity of 99.48% and specificity of99.83% were obtained based on evaluation on the MITDB. Though, there was too much experts' involvement in the ECG beats annotation process.

A Prenatal Detection of Congenital Heart Disease (CFD) was proposed by (Vullings et al. 2019). The study used a DNN model to detect CFD with 76% accuracy using private dataset containing fetal ECG measurements from 266 healthy and 120CHD groups. The performance may be improved with more population or dataset.

A study conducted in (Jeon, Chae, Han, & Lee, 2019) and (Jun, Park, Minh, Kim, & Kim, 2016) proposed a DNN models for arrhythmia classification and premature ventricular contraction (PVC) beat, respectively. The result indicated accuracy of 98.07% and 99.41% respectively using MIT-BIH Arrhythmia Database (MITDB). However,there was limited dataset for training and testing the models.

A study by (Cho et al. 2019) proposed a DNN model to detect stress using driving data and mental data. They recorded a performance accuracy of 90.19%. The data acquired from this study wasfrom specific stressful tasks. This can be improved for dailystressful monitoring. The model can also be used to detect anxiety which is a potential stressor to so many health challenges like high blood pressure etc.

A study by (Cai et al. 2020) proposed a modelbased on deep densely neural networks (DDNN) to detect Atrial Fibrillation (AF). In the study, only AF class was considered due to insufficient data in the other classes, the performance in terms of accuracy, specificity and sensitivity range above 99% using three dataset sources of 12-leadsECG including the China Physiological Signal Challenge 2018, the Chinese PLA General Hospital and wearable ECG devices from Cardio Cloud Medical Technology (Beijing) Co. Ltd, with 11,994 unique subjects.

Table 3: Summary of the Deep Neural Network applications in ECG

Reference	Deep learning structure	Application	Data	Accuracy	Limitation
(Xu et al.2017)	FDR+DNN	Arrhythmia classification	UCI cardiac arrhythmia(245 normal samples, 206 abnormal samples)	Acc=82.96% (FDR+DNN)	• Small number of samples anddata imbalance problem
(Chamatidiset al. 2017)	FT, DCT,WT +DL Neural network (DLNN)	Human Authentication	PTBDB (50 subjects)	DNN performed poorly on PTB because of insufficient databut performance increased from 86–97% with huge artificial ECG data-set	• Need for hugedata for training • The whole ECG signals should be used without performing preprocessing • Propose to incorporate cancelable biometrics techniques to minimize the risk of privacy violations
(Assodikyet al. 2017)	GA+ DL,PSO +DL	Arrhythmia Detection	UCI-ML Repository (452 data samples)	Acc=76,51% (PSO algorithm) and 74,44% (GA algorithm)	• Normal Sample data is muchhigher compared with other classes of signals
(Wieclaw et al. 2017)	DNN	Human identification	Lviv Biometric Data Set (18 subjects)	Acc=88.97%,	• The ECG distortions and small number of recordsper class affects performance. • Propose to use data augmentation based on generative model (GAN)
(Xu et al. 2018)	DNN	ECG Classification	MITDB (47 subjects)	Patient-specific classifierswith expert intervention and without expert intervention in parentheses **S class**:s Sen=66.2% (61.4%) Spe=98.6% (98.3%) **V class**: Sen= 90.5% (91.8%) Spe =98.1% (99.5%)	• Require large dataset for training •
(Sannino and De Pietro 2018)	Temporal feature extraction +DNN	ECG heartbeat classification	MITDB (47 subjects)	Acc=100% (training set)Acc =99.68% Sen=99.48% Spe=99.83% (testing whole data) Sen= 98.79%, Spe= 97.87% Acc=98.63%	• Too much Expert Involvement in the annotations process for the ECG beats • ECG is only classified as normal • and abnormal
(Cho et al. 2019)	(DNN)	Stressdetection	Driver stress data set, Mental Arithmetic Data Set (31subjects)	Acc=90.19% AUC=0.938	• Require large data for better performance • Workloador anxiety can be investigated usingproposed model • Datasets applied study were acquired during specific stressful tasks. However, daily stress monitoring is necessary
(Vullings et al. 2019)	DNN	Prenatal Detection of CHD	Private dataset with fetalECG measurements performed at six different medical centers in the (266	Acc=76%.	• There was limited population inthe study

			fromthe healthy group and 120 from the CHDgroup)		
(Cai et al. 2020)	DDNN	Detection of AF	Chinese PLA General Hospital, Dataset from Wearable ECG devices from the China Physiological Signal (CPS) Challenge 2018 (11,994unique subjects)	Acc = 99.35 ± 0.26%, sen = 99.19 ± 0.31%, spe = 99.44 ± 0.17% F1-score = 90.7%	• Only AF is detected due to insufficient data of other categories. • The influence of age for AF detection was negative, it can be verified further • Multi-class classification of different cardiac disease shall be investigated • Implementing the proposed model using wearable devices canbe investigated

VI. RECURRENT NEURAL NETWORK – LONG SHORT TERM MEMORY

Table 4 present the summary of the applications of LSTM in ECG. The application of LSTM in solving different ECG problems has been found in many researches and discussed as follows:

6.1.1 Long short term memory in ECG

The applications of the LSTM in ECG are presented in this sub-section, for example, a study based on LSTM model was conducted for OSA detection (Cheng et al. 2017). The model was tested on the Apnea-ECG database, having 70 ECG record and obtained detection accuracy of 97.80%.

A study proposed by (Salloum & Kuo, 2017) used RNN, GRU and LSTM models for identification/authentication. The LSTM model achieved the best performance with 100% accuracy on both MITDB and ECG-ID database. However, there were variations of ECG segmented window

A study presented by (Sujadevi et al. 2017) proposed RNN, LSTM, and GRU models for AF detection. Without any preprocessing method applied, the models achieved accuracy of 0.950, 1.000 and 1.000, respectively using AFDB and NSRDB from MIT-BIH Physionet.

A study presented by (Deshmane and Madhe 2018) proposed LSTM model for detection. Results show that precision of 0.91, sensitivityof 0.91 and F1 score of 0.90 were recorded. The performance of this model can be improved upon by providing a more robust preprocessing method.
Detection of AF using bi-LSTM was proposed by (Faust et al. 2018). The model yielded accuracies, specificities and sensitivities greater than 98% for both cross and blind validation.
A study proposed by Singh et al. (Singh et al. 2018), presented a study on RNNs basedmodels (RNN, GRU and LSTM). An accuracy of 85.4% (RNN), 82.5% (GRU) and 88.1% (LSTM) was achieved when tested on MITDB. However, hand-crafted features were use and it was not clear if the features will work on a new disease.
A study presented by (Yildirim et.al 2018) proposed a deep bidirectional LSTM-based model for ECG classification. This model proposed a wavelet-based layer to improve the classification performance using wavelet sequences (WS). The proposed DBLSTM-WS obtained thebest performance when WS layer is 3, with 99.39% on the MITDB. However, due to the hardware limitation not all dataset from the MITDB was used.
A study conducted by (Saadatnejad et al. 2019) proposed a LSTM model for ECG classification model was fed with RR features and wavelet features for training. The LSTM model was evaluated on the MITDB and achieved accuracy of 99.2% and 98.3% for VEB and SVEB, respectively.
In another study (Darmawahyuni et al. 2019) proposed RNN, LSTM and GRN models for MI classification. Among the proposed RNNs models, LSTM produced the best results with sensitivity of 98.49%, specificity of 97.97%, precision of 95.67%, F1-score of 96.32%, BACC of 97.56%, and MCC of 95.32% on PTBDB.
Another studyproposed by (Lynn et al., 2019) presented human identification task study using bidirectional GRU and bidirectional LSTM models. The models achieved accuracy performance of 98.55% (BGRU) and 96.4% (BLSTM)
MI classification was proposed by (Darmawahyuni and Nurmaini 2019) and used LSTM model to perform binary classification of MI. The model achieved precision of 0.91, sensitivity of 0.91, F1 score of 0.90 and BAcc of 0.83 using PTBDB.
A study presented by (Sharmaet al. 2020) proposed a LSTM model for arrhythmia classification. Fourier-Bessel expansion was used to derive the intelligent series from the RR-intervals and was fed intothe LSTM model

for classification. The model achieved an accuracy of 90.07% and 89.04% on MITDB and a private dataset, respectively

A LSTM model was proposed by (Chang et al. 2020) for the detection and classification of the cardiac arrhythmias. The model was found competitive compared with Cardiologists, emergency physicians and internal-medicine doctors. The model achieved 90% accuracy using ECG signals collected from the China Medical University Hospital (CMUH) recorded by a GE Marquette MAC 5500. However, the ST-T change which isimportant for diagnosing acute myocardial infarction was not detected.

Table 4: Summary of the Recurrent Neural Network applications in ECG

Reference	Deep learning structure	Application	Data	Accuracy	Limitation
(Cheng et al. 2017)	LSTM	OSA Detection	Apnea-ECG database (70 ECGrecords)	Acc =97.80%	• CNN should be explored
(Salloumand Kuo 2017)	RNN, GRU, LSTM	Human Identification/ Authentication	ECG-ID database (90 subjects) and MITDB (47 subjects)	Acc = 100% (LSTM), 96.8% (GRU) with MITDB,93.6%(RNN) with MITDB EER drops to 0% with 80% increase of subjects during training	• The model can be applied for cardiac abnormalities conditions classification
(Sujadeviet al. 2017)	RNN, LSTM, GRU	Detection of AF	AFDB (25 signals), NSRDB (25 signals)	Acc: 0.95(RNN),1.00(LSTM), 1.00(GRU) Pre: 1.00(RNN), 1.00(LSTM), 1.000(GRU) Recall: 0.889(RNN), 1.00(LSTM).1.00(GRU) F-score: 0.941(RNN), 1.00(LSTM), 1.00(GRU)	• Only binary classification was performed. • The model lacks showing theinner mechanics of the deep models, this can be solved by transforming the non-linearity to linearized form
(Shenfield, et al. 2018)	bi-LSTM	Detection of AF	AFDB (23subjects)	**Cross validation**: Acc = 98.51%,Sen =98.32%, Spe = 98.67%,Ppr = 98.39%. **Blind fold validation**: Acc = 99.77%,Sen =99.87%, Spe =99.61%, Ppr =99.72%	• Small number of population (data) used • Training speed during design phase was too slow • Only AF type is studied
(Singh et al. 2018)	RNN, GRU, LSTM	Classification of ECGArrhythmia	MITDB (47subjects)	Acc =85.4% (RNN), 82.5% (GRU), 88.1% (LSTM) Sen: 80.6% (RNN), 78.9% (GRU),92.4%(LSTM) Spe: 85.7% (RNN), 81.5%(GRU), 83.35% (LSTM)	• Only binary classification is Performed. • Manual features were used. • Not clear if the proposed features will perform well onnew diseases
(Yildirim 2018)	DBLSTM -WS	ECG classification	MITDB (47subjects)	Acc =99.39%	• Not all heartbeat from MITDB were used due to limitation of hardware • Training cost problem
(Lynn et al. 2019)	BGRU, BLSTM	Human Identification	ECG-ID Database (90 subjects) and MITDB (47 subjects)	Acc =98.55%(BGRU), 96.4% (BLSTM)	• The model takes time to train the data • Varia tion in the ECG segmented window. • The effect of large scale datasets using diverse datasets should be investigated

(Saadatnejad et al. 2019)	RR featur esand wave- let featur es + LSTM	ECG Classification	MITDB(47subjects)	VEB Acc = 99.2 Sen = 93.0 Spe = 99.8 Ppr = 98.2 F1-score = 95.5SVEB Acc = 98.3 Sen = 66.9 Spe = 99.8 Ppr = 95.7 F1-score = 78.8	• Limited dataset for training
(Darmawahyuni et al. 2019)	RNN, LSTM, GRN	Classificationof MI	PTBDB (290 subjects)	LSTM results sen,98. 49% spe,97. 97% precisi on, 95.67 %, F1-score, 96.32% BACC, 97.56%, and MCC 95.32% (best performance)	• Initial performance wasaffected due to minimal preprocessing
(Darmawa-hyuni and Nurmaini 2019)	LSTM	MI Classificati on	PTBDB (290subjects)	Pre = 0.91, Sen = 0.91, F1 score = 0.90, BAcc = 0.83, and MCC = 0.75	• The proposed model is simpleand standard • Performance was not good enough due to minimal preprocessing
(Sharma et al. 2020)	FB expansion +LSMT	Arrhythmia classification	MITDB (2880 segments), PhysioNet/ CinCChallenge 2017 dataset (8528 segments)and privatedataset (301 segments)	Acc & F1 score = 90.07% (MIT-BIHdataset) Acc = 89.04% Sen = 75.68% Spe = 93.39% F1-score = 85.01% (private dataset)	• Only two classes, normal and arrhythmic were detected. • Signal quality assessment not applied before classification. • More ECG signals needed to improve arrhythmias identification accuracy. • Limited to rhyme based analysis wherein morphological features were difficult to detect
(Chang et al. 2020)	LSTM	Detection and Classification of Cardiac Arrhythmias	Dataset from China Medical University Hospital (CMUH) recorded by a GE Marquette MAC 5500 (38,899 subjects)	Acc ≥ 0.982 (range: 0.982–1.0) precisionranged from 0.692 to 1 recall ranged from 0.625 to 1 F1-score of ≥0.777 (range: 0.777–1.0).	• The model did not detect ST-Tchange which is but only predict the 12 rhythm classes. ST-T change is important for diagnosing acute myocardial infarction. • ECG noise may affect the performance of the proposed model negatively • More data is required for testing and training. The imbalance data problem • Increased computational costdue to QRS detection

VII. DEEP BELIEF NETWORK

The DBN has been used in diverse ECG to solve various problems.In this section, we present different works involving DBN and summary of the projects is presented in Table 5.

7.1.1 Deep Belief Network in ECG

The researches that applied DBN in ECG are presented in this sub-section. For example, RBN model was proposed by (Mostafa et al. 2017) for sleep apnea detection. The model achieved accuracy of 85.26% on the UCD database and 97.64% on the apnea-ECG database. However, the model was tested with imbalanced dataset.

A study for arrhythmia detection was proposed by (Altan et al. 2018) using a multi-stage DBN model; a greedy layer-wise unsupervised and supervised training RBM-DL. Techniques such as higher order statistics, morphology, Wavelet packet decomposition and Discrete Fourier transform were used for featured extraction. The model achieved performance of 94.15% accuracy, 92.64% sensitivity and 93.38% selectivity on MITDB. However, the comparison was difficult due to different number of heartbeats.

RBM-DBN model was proposed by Mathews et al. (Mathews et al. 2018) for ECG classification. The proposed model was evaluated on the MITDB and achieved accuracy of 93.78% (SVEB) and 96.94% (VEB) on the sampling rate of 360 Hz. And using the sampling rate of 114 Hz, accuracy of 93.63% (VEB), and 95.57% (SVEB) was achieved.

Table 5: Summary of the Deep Belief Network applications in ECG

Reference	Deep learning structure	Application	Data	Accuracy	Limitation
(Mostafa et al. 2017)	DBN	Sleep Apnea Detection	St. Vincent's University Hospital/University collage Dublin Sleep Apnea data base (UCD database), 8 subjects physionet apnea ECG-database (Apnea ECGDB) (25 subjects)	Acc = 85.26% UCD database (Apnea ECG database) Acc = 97.64%, (Apnea ECGDB database)	• Imbalanced data problem Hidden layers neurons ware only optimized for UCD database • The structure of DBN was fixed • Small population was used
(Altan et al. 2018)	Morphological features, HOS, WPD, DFT + DBN	Detecting Arrhythmia	MITDB (48 subjects)	Acc = 94.15%, sen = 92.64%, Selectivity = 93.38%	• Comparison difficulty because of different number of heartbeats from different subjects • Require more data fortraining
(Mathewset al.2018)	RBM-DBN	ECG classification	MITDB (48 records)	Acc = 93.78% (SVEB), 96.94% (VEB) Sampling rate ơ 360 Hz. Acc = 93:63% (VEB), 95:57% (SVEB) sampling rate of 114 Hz.	• Proposed theintegration of RBM with ensemble based/Bagging method to develop multiple individual classifiers in the future

VIII. AUTO-ENCODERS.

In this section, we present different AE proposed by different researchers in solving problems in ECG. Table 6 present the summary of the AE application.

8.1.1 Auto-encoders in ECG

A study presented by (Luo et al. 2017) proposed SDAE model for patient-specific ECG classification. The authors first converted the raw ECG signals into time-frequency image using modified frequency slice wavelet transform (MFSWT) which was fed into the SDAEfor feature extraction. The model used the encoder layer of SDAE and a softmax layer to form a DNN model for the classification. The model produced classification accuracy of 97.5% when evaluated on the MITDB.

An ECG-biometric based on AE was proposed by Eduardo et al. (Eduardo et al. 2017). The proposed method was tested on a private dataset collected from a local hospital using a Philips Page Writer Trim III device from 709 subjects.The model achieved a good performance. The performance of the proposed method can be improved by employing more robust preprocessing methods. Classification of AF based on stacked AE model was proposed by (Farhadi et al. 2018). Statistical test, Analysis of Variance (ANOVA) was used to evaluate the extracted features. From our review, a single study was found to have proposedAE-based model to model ECG signals.

The study proposeda driver fatigue classification using deep AE (Bhardwaj et al. 2018). Data was collected using 10 subjects recorded during driving simulator and achieved accuracy of 96.6%. A Multimodal system integrating bio-signals (ECG, EEG and EMG) was suggested for robust driver fatigue system.

A study presented by (Al-Rahhal et al. 2018) also proposed SDAE network for learning feature representation from ECG data. Consequently, a softmax regression layer was added unto the SDAE network for automatic classification of Premature Ventricular Contractions (PVC). An overall accuracy of 98.6% was achieved on the INCART dataset.

Ojha et al., 2022, implemented a 1D-CNN model based on an Auto-encoder Convolution Network (ACN). A good accuracy of 99.53%, sensitivity of 98.24% and specificity of 97.58% were obtained based on evaluation on the MIT-BIH

Table 6: Summary of the Auto-encoders applications in ECG

Reference	Deep learning structure	Application	Data	Accuracy	Limitation
(Luo et al. 2017)	MFSWT + SDA	ECG Classification	MITDB (48records)	Acc = 97.5%	• The proposed method is computationally expensive
(Eduardo et al. 2017)	AE	User identification	Data collected from local hospital using a Philips page writer Trim III devices(709 subjects)	Identification error B: 4.24 Mi:1.24, M2:1.24, M3:0.91	• Other processing methods can be investigated • Exhaustive search can be performed on thehyper parameters
(Bhardwaj et al. 2018)	DAE	Driver fatigue classification	Private data collected using Simulator-based monotonous driving environment (10 subjects)	Acc = 96.6%	• Require more data for training, testing and validation • Multimodal system integrating bio signals (ECG, EEG and EMG) can be considered for a robust driver fatigue system
(Farhadi et al. 2018)	ANOVA + SAE	Classification ofAF	MITDB(47subjects)	Acc: 93.6%	• Small dataset was used
(Al Rah- hal et al. 2018)	SDAE + DNN	PVC detection	MITDB, INCERT, SVDB, (21subjects)	Acc: 98.6% Sen = 91.4%, Ppr = 97.7%	• Only binary classification is Performed. • Manual features were used. • Not clear if the proposed features will perform well onnew diseases
(Ojha et al., 2022)	CNN-SVM	ECG classification	MIT-BIH(4subjects)	Acc: 99.53% Sen = 98.2.4%, Spe = 97.58%	• class unbalances • limited access to rich databases

IX. GENERATIVE ADVERSARIAL NETWORKS

In this section, we present only paper that applied GANs-based model for ECG signal analysis. Table 7 present the summary of the GAN application.

Zhou et al. 2020 proposed GAN with Auxiliary Classifier for ECG (ACE- GAN). This model also addressed the problems faced by most of the DL architectures, such as CNNs on handling imbalance data and poor performance due to limited labeled ECG data. These problems have been investigated in the literature; however, the proposed methods still faced some challenges. For instance, labeling patient-specific heartbeats have been proposed to enhance classification performance. However, the systems were not fully automatic and there were too much experts' involvements.

Table 7: Summary of the Generative Adversarial Networks applications in ECG

Reference	Deep learning structure	Application	Data	Accuracy	Limitation
(Zhou et al. 2020)	ACE-GAN	ECG arrhythmia classification	MITDB(47subjects)	**SVEB** Acc: 99% Sen: 85% Spe: 99% Ppr: 85%F1:85% **VEB** Acc:99% Sen:93% Spe: 99%Ppr:90% F1:91%	• Require large data-set for training • Only two ECGclasses of beats were considered

X. CHALLENGES AND FUTURE RESEARCH DIRECTION

The adoption of deep learning architectures in Electrocardiography has brought a lot of benefits. Given the attention attracted by the extensiveness of the research area, there are unresolved challenges. The challenges are discussed and future research directions with new perspective are outlined to facilitate future development of the research area:

10.1 RESOURCE MANAGEMENT AND ACCURACY CHALLENGES

The development of healthcare applications that monitor a patient in real time, alerting physicians in real-time to provide better assistance at the right time is highly necessary. Health and medical care applications are considered as one of the most fascinating applications that can fully benefit from the IoTs deployment. Although there are studies that have implemented DL to process ECG signals for edge computing and IoTs deployment (Azimi et al., 2018; Konan & Patel, 2018) (Farahani, Barzegari, & Aliee, 2019) (Granados, Chu, Zou, & Zheng, 2019). However, requirements of latency, low power and knowledge extraction from the large volume of physiological data are challenge for real time applications. As an open research direction, edge computing environment, modern AI techniques combined with 5G speeds are needed to meet the necessary requirements for the latency, accuracy and energy efficiency during real-time collection and analysis of health data (Hartmann, Farooq, & Imran, 2019). Therefore,applications of DL on ECG based systems can be developed and deployed on the cloud computing-based-environments, such as edge computing, software-defined computing, fog computing, mobile edge computing, serverless computing and volunteer computing to enable ubiquitous and remote health monitoring (Buyya et al., 2018; Varghese & Buyya, 2018).

10.2 DATA SET CHALLENGES

Data is the heart of deep learning operations, without data, deep learning algorithm becomes impotent. Based on our review, we identified more than 40 datasets that have been used in modeling DL to analyze ECG signals for different classification tasks. It can be deduced that MITDB, PTBDB, AFDB, physionet/CinC Chanllenge 2017, NSRDB, ECG-IDDB and CYBHi-DB have received the highest number of usage. All these datasets are available online and can be accessed via the internet. However, the number of private datasets indicates their non-availability on the internet for public use. This had forced the authors to acquire it themselves with additional resources. More so, the commonly used dataset is MITDB (Moody et al. 2001), which is over 40 years and contains only records from 47 subjects and is grossly imbalanced. In addition, this database is a single session database, which is not adequate for experiments on biometrics (Hammad et al. 2019). The recent datasets used are PhysioNet/CinC Challenge 2017 (Clifford et al. 2017) and 2018 China Physiological Signal Challenge (Liu et al. 2018), but these database were recorded on short-term durations. DL are data-driven, DL require large scale data for training (Qayyum et al. 2019). Tables 2, 3, 4, 5, 6, and 7 presented limitations for each of the studies. Generally, it shows that the datasets used to trainthe models were not large enough to give a better generalization. In a bit to address the problem of imbalanced and small dataset in most of the existing databases, studies have been proposed such as data augmentation (Giannakakis et al. 2019) Hammad et al. 2018; Hammad and Wang 2019; D. Li et al. 2019) (Shaker et al. 2020) and transfer learning (Pan and Yang 2009; Weiss et al. 2016). Techniques such as SMOTE (Pandey and Janghel 2019) (Chu et al. 2019) and GAN (Shaker et al. 2020), were used to solve the problem of imbalance dataset. Therefore, it is recommended that large scale datasets should be produced for all the domains discussed in this paper. These datasets should be made available online to encourage researches and ease the data acquisition process.

10.3 APPLICATION TASKS CHALLENGES

There are different tasks executed by the DL models discussed in this review. We considered models based on their respective task. The models in each of the domain discussed have different targets to achieve during modeling. Figure 9 presented the taxonomy of these tasks and categorized based on domains. For example, in biometric ECG based systems, the model performed authentication for a user, to either allowed access or denied. However, there are still challenges of inter-subject and intra-subject ECG variability in biometric ECG based systems. The inter-subjects variability deals with the uniqueness issues and intra-subject deals with the permanence issues, that affect the system by factors such as heart geometry, individual attribute, medication, cardiac condition, posture, emotion, age and fatigue, electrode characteristics and placement (Abdeldayem and Bourlai 2019; Carreiras et al. 2016; Pinto et al. 2018). These challenges remain open issues for ECG-biometric based systems. Also, some studies performed classification task on whether an instance exist or not. For example (Swapna, Kp, et al., 2018; Swapna, Soman, et al., 2018) classified ECG signals as diabetes or non-diabetes and nor-mal or arrhythmia, respectively. (Shashikumar et al. 2018) classified as PAF or normal, (Yuan et al. 2016) classified as AF or normal, (Wang et al. 2019) classified ECG as normal or abnormal, (Vullings 2019) performed prenatal detection of CHD as CHD or Healthy, (Tan et al. 2018) classified CAD as normal or CAD, (Mostafa et al. 2017) classified apnea as apnea or not apnea (Taherisadr et al. 2018) detected driver's in attention as distracted or not distracted and so on. Other studies classified output into groups or level of instances. For instance, (Abbas 2020) performed driver's drowsiness detection as drowsy, sleepy and normal, (Luo et al. 2017) classified ECG beats into 5 classes. A study by (Urtnasan et al. 2018) performed apnea/hyponea detection as Normal, Hypopnea, Apnea, etc.

10.4 Deep learning and related challenges:

Although existing studies on ECG signal processing and diagnoses have focused more on the application of traditional machine learning approaches, recent advancement in automated feature extraction of ECG characteristics using deep learning methods has attracted a great deal of attention in the research community. Nevertheless, the predictive accuracy of these deep learning models still needs to be improved to be on par with the traditional machine learning approaches. Future studies can consider hyper parameter optimization techniques to improve the predictive performance of deep learning models for ECG signal processing. There is a need to develop a lightweight deep learning model that is clinically viable and can be deployed on mobile applications for ease of use. Model generalization problem with patients of different races is also another research issue to be considered in future studies. Although this problem is not only limited to deep learning models, however, the capability to learn from large number of clinical databases can be of significant benefit to address this problem. In addition, adversarial samples can lead to misbehaviors of deep learning models. It is crucial to test the model's robustness and protection against adversarial attacks.

XI. CONCLUSIONS

The paper proposes to conduct an in-depth literature survey on when deep learning architecture in electrocardiography including synthesis and analysis. The survey examines the performance of application of deep learning in ECG from the last decade and justifiably so, especially for medical and healthcare application. It is found that the applications of deep learning in modeling ECG data has proven to produce state-of-the-art performances and even more accurate performances than the experienced Cardiologists. However, apart from the well-known challenges of limited dataset and computational cost required by the DL applications, other challenges, such as security of applications, latency, low power and knowledge extraction from the large volume of physiological data for real time applications and the "black box" nature of DL models were also highlighted to enable room for future development. This study can serve as a benchmark material for new researchers to further improve the performance of the existing DL in modelling ECG signal.

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