A Comprehensive Review on Arrhythmia Classification using Deep Learning Methods

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National Conference for doctors of HAL on May 2022 published in its report that, India will record the maximum number of deaths due to cardiovascular diseases (CVDs) by 2030 in the world. So its timely detection and cure can save many lives. To detect and classify CVDs, deep learning (DL) methods are widely used. This survey focuses on a variety of DL models applied in various research papers, to find models with higher accuracy in the classification of arrhythmia and other heart-related issues. Here six DL models have been focused namely Convolution Neural Network (CNN), Gated Recurrent Unit (GRU), Long Short Term Memory (LSTM), Multi-Layer Perceptron (MLP), Deep Belief Network (DBN), and Recurrent Neural Network (RNN) after the review of 23 papers from the year 2018-2022, to find the suitable model for classification task and feature extraction where Electrocardiogram (ECG) is a common input to the every DL model.

Keywords: Arrhythmia classification, Deep Learning methods, cardiovascular heart diseases, biomedical signal processing.

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1 Introduction

The alarming fact as per the reports of Global Burden of Disease is that approximately 25% of deaths are due to heart-related ailments. The classical approach to the diagnosis of Cardio Vascular Diseases (CVDs) is primarily based on the medical history of the patient and various clinical tests where test results are expounded by the medical experts. At times it is desirable to have an accurate result, especially in the analysis of the Electrocardiogram (ECG) waveform since a slight variation may provide a different interpretation leading to inappropriate treatment. Hence an urge of developing a system where an accurate diagnosis can be performed is quite evident. To develop such a system, Deep Neural Networks (DNNs) can be used. Since DNNs show promising results over traditional methodologies, here a wide range of DNNs are reviewed.

1.1 Challenges in ECG Signal recording

i. ECG signal waveform may vary for different persons. It is a challenge to generalize the properties of ECG. Hence drawing common rules may not work [1].
ii. Capturing a signal can also be a problem. Since it may add noise to an original signal leading to inappropriate results [2, 3].
iii. The same person may have a different pattern of ECG because of his physical state such as resting, jumping, etc.
iv. Duration of ECG also matters. One should record ECG for a longer time to achieve accurate results.

1.2 Deep learning techniques

Deep learning as the name suggest goes deeper into the network, i.e. adding layers to the network to learn from data. This technology is quite advanced from traditional approaches since here the human intervention is quite less because here the feature selection is dependent upon the network in contrast to the traditional methods where handcrafted features are being given to the system. This feature makes deep neural networks more independent and accurate [4, 5]. Owing to this benefit, many researchers have developed interesting deep nets, be it CNN, LSTM, U NET, or ALEXNET with so many in the queue. Every deep net has its characteristics. Our focus here is to study those nets which takes biomedical signal esp. ECG as input and classify arrhythmia with good accuracy [6]. Following are the popular deep neural networks:

1.2.1 Multilayer Perceptron (MLP)

MLP is an example of an artificial neural network that works in a forwarding direction. The minimum MLP contains at least 3 layers. One is the input layer the next one is the middle layer which can be said as the computation layer and finally the output layer which shows the result. In each layer, every perceptron has a weight associated and each network uses a threshold activation function [4].

1.2.2 Convolutional Neural Network (CNN)

CNN undoubtedly can be said as a backbone of Deep nets. Generally, a gradient-based algorithm is used to train the CNN [7]. This network contains many layers and each layer has dedicated work to perform. It starts with an input layer, stepping towards the convolution layer, then a normalization layer in addition to the pooling layer, and finally a fully connected layer before the final output layer. It has a wide variety of applications which showcases its efficiency [8]. Fig. 1 shows the CNN model which takes the ECG signal as an input. Here multiple layers of Convolution and max-pooling are used to extract important features of ECG and classification is performed to achieve output [49].

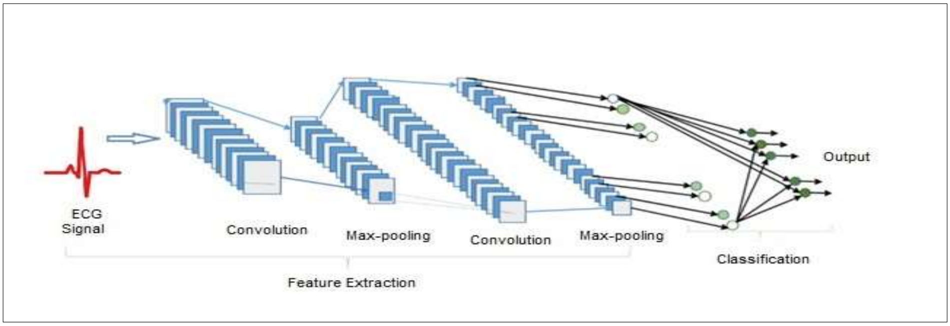

Figure 1. Convolutional Neural Network (CNN) with ECG signal as input
Image Source: Zahra(2020). A review on deep learning methods for ECG arrhythmia classification

1.2.3 Deep Belief Network (DBN)

A deep belief network is a discriminative model based on auto-encoders proposed by Hinton in 2006 [9], with layer to layer connection approach. DBNs work efficiently for unsupervised learning problems since it works on dimensionality reduction but can also be used efficiently for supervised learning tasks for the problem of regression or classification. Training a DBN is a 2 fold process. The first step is to train each Restricted Boltzman Machine (RBM) in an unsupervised manner. After finishing this layer-to-layer training, the next step is to fine-tune the parameters with the use of backpropagation algorithms. Fig. 2 illustrates the architecture of DBN. The figure has an input layer that takes the ECG signal as an input. It also has RBNs along with a classifier that segregates the output into two labels.

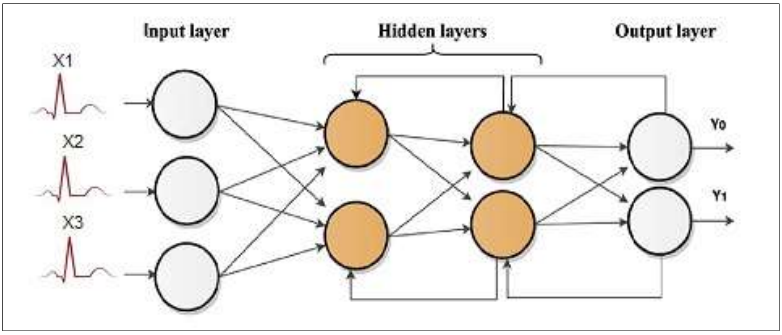

Figure 2. Deep Belief Network architecture

1.2.4 Recurrent Neural Network (RNN)

A special case of the artificial neural network is a Recurrent neural network where weight sharing is time-dependent. The learning is based on feeding the current input to the network again along with the feedback resulting in the addition of values to the memory [10]. With help of a gradient descent algorithm, training has been provided to the weights. It has an input layer, a hidden layer that gets updated and provides prediction. These networks work perfectly for ordinal or temporal data. Fig. 3 illustrates the architecture of RNN. The figure has an input layer, hidden layers, and an output layer. The hidden layer is recurrent in nature.

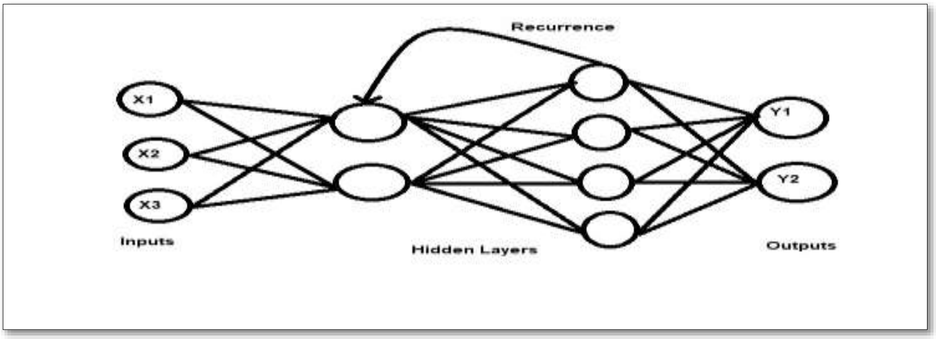

Figure 3. Recurrent Neural Network architecture

1.2.5 Long Short-Term Memory (LSTM)

A variety of Recurrent Neural networks is LSTM which is used for long-range dependencies and temporal sequences [11]. This network can efficiently deal with the problem of vanishing gradient descent. This network works in three segments, the first segment is named as Forget gate which decides the information to retain or to forget, the next segment is known as the input gate which learns new information and the final one is the output gate where the updated information is passed from the current timestamp. (Fig. 4) illustrates the architecture of LSTM. This figure

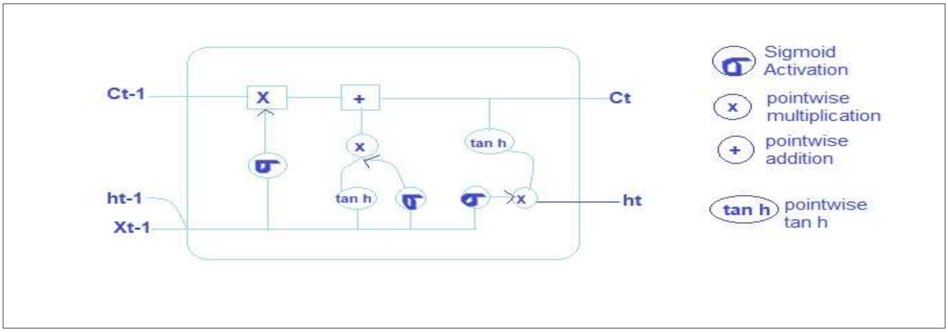

Figure 4. Architecture of LSTM

1.2.6 Gated Recurrent Unit (GRU)

The advanced version of LSTM is GRU as it has a faster training process with quite less computational complexity (Fig.7). It has a combined forget and input gate to form a new gate as an update gate. This gate functions on balancing the state between past and present activations. Fig 5 shows the architecture of GRU. It has two gates update and reset. The update gate retains the past knowledge and reset gate erases the past knowledge.

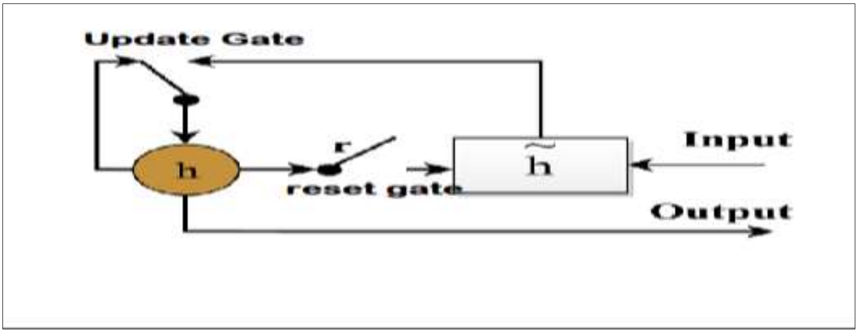

Figure 5. Architecture of GRU
Image Source: Rana R (2016). Gated Recurrent Unit (GRU) for Emotion Classification from Noisy Speech

2 Cardiovascular Disease categorization

In this section, a brief overview of different heart ailments has been given which can be figured out by ECG signal. Diagnosis of heart disease by the study of electric impulses [12]. To check whether the electric activity is regular or not, measurement of time intervals on ECG is required. Time interval shows how much is required to generate and pass electrical activity which can be traced out in the form of a waveform. ECG also shows the strength of a signal. Which is basically perceived as the work done by a heart to perform its task. Fig. 8 depicts a normal heartbeat which shows all segments and all the associated waves which show atrial depolarization (P-wave), ventral depolarization (QRS segment), and finally repolarization (T segment). Following are the most common type of irregularities in the heartbeat:

2.1 Atrial Fibrillation (AFib)

It is the phenomenon where atria are working at a very high speed i.e. a heart is beating roughly at a speed of 100-125 beats/minute. Due to this P wave gets neglected [13]. Fig. 6 shows the condition of AF.

Figure 6. AF

Figure 7. RBBB

Figure 8. LBBB

2.2 Right Bundle Branch Block (RBBB) and Left Bundle Branch Block (LBBB)

It is a situation where electrical impulses cannot travel on their pathways due to blockage resulting in improper formation of a heartbeat. At times pumping blood to the rest of the body also gets difficult. In case of left bundle branch block electrical impulse travel right bundle branch to the right ventricle, thereafter to the left ventricle via a septum. In the case of RBBB, a delay occurs in the RV because depolarization is sourced from LV across the septum. Resulting generation of a second R wave in precordial leads and a deformed S wave [14]. (Fig. 7 and Fig. 8) shows the condition of RBBB and LBBB respectively.

2.3 Premature Atrial Contraction (PAC) and Premature Ventricular Contraction (PVC)

It is the condition of an untimely appearance of a beat resulting in a disturbed heart rhythm. It can be of two forms:
a. If a beat occurs from the ventricle, it is said as Premature Ventricle Contraction (PVC)
b. If beat emerges from atria, it is then said to be Premature Atrial Contraction (PAC)

Figure 9. Ectopic Beats

Figure 10. MI

Figure 11. Sinus Bradycardia

2.4 Myocardial Infarction (MI)

The most common and dangerous disease is Myocardial infarction commonly known as Heart attack arises when the flow of blood drops to zero, making heart muscle damaged. (Fig.10) shows Myocardial Infarction).

2.5 Ectopic beats

Ideally, the action potential should arise from the sinus node but this is not the case when the patient is dealing with ectopic beats. In this phenomenon the action potential arises before the sinus node hence providing a weak heartbeat which makes a smaller almost negligible P wave (Fig. 9). Highly stressful tasks and bad food intake may also lead to ectopic beat issues [13].

2.6 Fusion beat

It has two types, one is ventricular fusion beats. This gets generated in the ventricle when a variety of sources takes action at the same time in the same area of the heart. In contrast to this atrial fusion, a beat occurs in the atria due to a variety of beats happening at the same time [15, 16].

2.7 Sinus bradycardia and Tachycardia

The normal heart rate for an adult ranges from 60 to 100 beats per minute. If the heart rate goes lower than this then the disease is named bradycardia. Symptoms of bradycardia are vertigo, dizziness hypotension, and many more [17] (Fig. 11). On the contrary, if the heart rate shoots up more than 100 beats per minute then it is said to be tachycardia [18] (Fig. 9). Depending upon the position where the heart rate increases tachycardia can be classified accordingly. If the heartbeat gets faster in the atria then it is said to be Atrial or Supraventricular Tachycardia. (Fig. 12), if it is happening in the sinus node then Sinus Tachycardia lastly Ventricular Tachycardia is caused in the ventricles [19].

2.8 Atrial Flutter (AFL) and Ventricular Flutter (VFL)

Fluctuating heart rate results in Flutter. So in the case of Atrial Flutter irregular heart rate is caused in Atria. Contrary to this ventricular flutter happens when non uniform heart results tachycardia which may lead to death also [19] (Fig. 13).

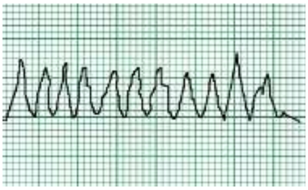

Figure 12. Tachy Bradycardia

Figure 13. Atrial Flutter

Figure 14. VFib

2.9 Ventricular fibrillation (VFib)

A variety of arrhythmia where the heart starts trembling in place of pumping. This condition known as Ventricular fibrillation is quite dangerous and it may lead to death if proper treatment is not taken on time [20, 21]. The ECG waveform also gets disturbed resulting in an amorphous QRS complex and almost negligible P wave. (Fig. 14)

3 Databases

Most of the research papers, used in this review work, have taken some popular databases to get more accurate results and better informed decisions. Naming few of them are MIT – BIH arrhythmia database, PhysioNet, and many more. Table 1 has systematic information about all the used databases. The first column tells about the databases which were used in quoted research works, and the second column tells about the number of recordings taken from each database. The third column shows sampling information. The final column includes the diseases for which data was collected.

Table 1. Popular Databases used for arrhythmia classification

Database Name	Number of Recordings	Data Sampling Information	Included Disease
PhysioNet	310 ECG recordings	Digitalized at 500 Hz with12-bit resolution	Atrial Fibrillation(AFib)
The MIT-BIH	25 long-term ECG recordings	250 samples with 12 bit resolution	Atrial Fibrillation(AFib)
Creighton University	35 eight-minute ECG recordings of human subjects	Digitalized at 250 Hz with 12-bit resolution	Pulseless Ventricular Tachycardia and Ventricular Fibrillation
The MIT-BIH Malignant Ventricular Arrhythmia Database	22 ECG recordings each with a half hour	Digitalized at 250 Hz	Pulseless Ventricular Tachycardia and Ventricular Fibrillation
E-HOL-03-0202-003 (Intercity Digital Electrocardiogram Alliance'IDEAL) Database (According to University of Rocher Medical Center & Warehouse, 0000)	202 subjects(healthy) 24 Holter recordings	Sampling Frequency: 200Hz	Healthy ECG signal
The PAF Prediction Challenge Database [36]	50 record sets	Digitalized ECGs (16 bits per sample)	PAF
PTB- XL Dataset	Set of 21, 837 records		MI

4 Performance measurements

This section states important measurements used in a variety of research papers to quantify their work in terms of performance. Some measures are indicated below [22].
True Positive shows if the person has the disease and is predicted positively.
True Negative shows if the person does not have the disease and the result comes out as false.
False Positive shows that the person does not have the disease but the result shows he has the disease.
False Negative implies that a person has the disease but the results are negative.

Table 2. Evaluation Category

	Has the disease	**Does not have the disease**
Positive result	True Positive (TP)	False Positive (FP)
Negative result	False Negative (FN)	True Negative (TN)

$$Accuracy(AC) = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Specificiy(Spft) = \frac{TN}{TN + FP}$$

$$Sensitivity(Snvt) = \frac{TP}{TP + FP}$$

$$Precision(P\ value) = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F_1(or\ F\ Score) = (\frac{Recall^{-1} + Precision^{-1}}{2})^{-1}$$

5 Research methodology

This study revolves around 2018 to 2019. Journals have been picked with ECG-related backgrounds along with deep learning techniques in them. All the references have been included from Google Scholar and PubMed. The study has two different dimensions: One is where the variety of deep learning networks have been showcased and their performance has been recorded as a classifier or as a feature extractor. On the other hand variety of arrhythmia has been classified.

6 Results of this Research Work

This paper has been organized into 4 sections: The first section features various deep neural networks as a feature extractor. The second section introduces papers where a deep neural net has been used as a classifier. In the third section deep has been used as a classifier and feature extractor (table) and finally, the fourth section has taken a variety of arrhythmia. A study of a total of 64 papers have been included in this research work. Results of the finest research have been put up here in detail. Tables 2-6 give a brief review of work that has been done in a different direction towards the same goal under the umbrella of deep learning.

6.1 MLP Variants

Sannino et al. [23], in their research paper, developed a new Deep Learning model which uses 5, 10, 30, 50, 30, 10, and 5 neurons in 7 layers respectively. It has ReLU activation function and cross-entropy as cost function and on the output layer, Softmax has been used. This model can classify NSR, SVEB, and a combination of ventricular and NSR with the accuracy of 100% for training data, 99.09% for test data and 99.68% for the total data. Pan et al. [25] used the Hidden Markov model (HMM) and DNN to classify Sleep Apnea on a single lead ECG. It uses DNN for feature extraction and classification is being performed by SVM and ANN.

6.2 CNN Variants

As mentioned earlier CNN is the most commonly used neural network because of its features and performance. Here are some top-performing research works that have taken CNN as a base model. Starting with a model proposed by Tin et al. [39] which classify VEB and SVEB with an accuracy of 98.6% and 97.6% respectively. It takes an ECG signal as an input and a single heartbeat capturing method for feature extraction. With the database of MIT-BIH arrhythmia. Another good model proposed by Zhang et at. [42].This model shows an accuracy of 98.29% with the first architecture and 98.63% for the second architecture for the classification of Atrial Fibrillation. This model uses two deep nets one with Short Term Fourier Transform (STFT) and CNN with 11 layers and the other with (Stationary Wavelet Transform) SWT and CNN with 10 layers. Table 2 shows the performance of variety of CNN.
The table has multiple columns. The first column shows the reference of research papers. The second column shows the applicability of quoted research works. The third column gives information about which model is used for feature extraction and the model is used for classification. The fourth column dictates the databases used and the final column is used to showcase the results of the research works quoted in this paper.

Table 3. Performance of Variants of CNN

Reference	Application	Method		Database	Results
		Feature Extraction	Classification		
Liao et al. (2018)[37]	Fetal QRS segment detection	CNN+FCNN		PhysioNet/Computing in Cardiology Challenge 2017 2013	$F1$-score:77.85% Recall:80.54% P Value:75.33%
Deng et al. (2018) [38]		Gstreamer and getframe technology	Convolution Neural Network	Physiobank ECG-IDdb 2017 PhysioNet/Computing in Cardiology Challenge 2017 2017	NSR (50): AC = 96.63%, Atrial Fibrillation(50) : AC = 96.23%, Noise level (50): AC = 96.18%,
Tin et al. (2018) [39]	Ventricular ectopic beats and Supraventricular ectopic beat	Single Heartbeat capturing	Convolution Neural Network	MIT-BIH Arrhythmia Database	Ventricular ectopic beats: AC= 98.6% Snvt: 93.8% Spft: 99.2% Supraventricular ectopic beat: AC= 97.6% Snvt= 76.8% Spft= 98.7%
Özal et al.[29] & Acharya et al.[40]	Premature Beats in APB, AFib, SVT, PVC, VFib, VT, NSR, RBBB, LBBB.		Convolution Neural Network + Fully Convolution Network	MIT-BIH Arrhythmia Database	AC= 91.33%
Jin et al. (2018) [41].	PVC	Epi-Endo CNN	FCN	90 PVC beats from 9 patients with PVCs	Segment CNN AC=78% Epi-Endo CNN AC: 90%

Zhang et al. (2018) [42].	AFib	(STFT) (SWT)	CNN DeepNet1 (STFT + CNN DeepNet2 (SWT+CNN)	MIT-BIH Arrhythmia Database for AF	DeepNet1: Snvt =98.34% Spft =98.24% AC= 98.29% DeepNet2: Snvt=98.79% Spft=97.87% AC= 98.63%
Wang et al. (2018) [43]	Fatal Heart Monitoring	CNN	FCN	Customized Database	P Value =94.71% Recall: 94.68% AC = 94.7%
Emamian et al. (2018)[44]	NSR VT AFib Ventricular Bigeminy	CNN	FCN	PhysioBank	Arrhythmia AC= 88% NSR AC= 87%
Nguyen et al. (2018)[45].	Recognition of 8 pattern images (signal pictures)	Transform into 128 *128 Gray-scale image	AlexNet VGGNet	MIT-BIH Arrhythmia Database for AF	AC=: 99.05%, Snvt = 97.85%
Mahajan et al. (2018) [46].	NSR AFib Other Abnormal Rhythms	1. 62 features from a combination of descriptive, linear, nonlinear, temporal and spectral statistical methods 2. raw signal	1. MLP 2. CONVOLUTION NEURAL NETWORK	PhysioNet/Computing in Cardiology Challenge 20172017	1. AC= 76.79% f 1 -score: NSR: 0.84, AF: 0.63, Other Abnormal Rhythm: 0.63 2. AC = 74.84% f 1 -score: NSR: 0.84, AF 0.69, Other Abnormal Rhythm: 0.60
Chen et al.(2020)[51]	NSR AFib		CNN+LSTM	MIT-BIH Arrhythmia Database for AFib	NSR: 1. AC= 99.7% Snvt= 99.36% Spft=99.94% AF: AC=98.12% Snvt=94.83% Spft=97.74%

6.3 DBN Variants

Table 4 shows a brief overview of the promising architecture of deep belief that ensures good performance for classification tasks. Due to this feature, many of researchers have used this model for their arrhythmia classification task. Naming a few of them here, Kadambari et al. 2018 [24] have designed a model which uses Gaussian- Bernoulli along with Deep Belief Network. This model guarantees the accuracy of 99.5% and 99.4% for SVEB and VEB respectively with the database of MIT-BIH. Considering another top-performing model proposed by Taji et al. 2018[27] reduces the false alarm rate due to poor quality measures in the detection of Atrial Fibrillation. It has 3 layers of RBM, the first 2 involve generative RBM and the third one has discriminative RBM.

Table 4. Performance of Variants of DBN

Reference	Application	Network		Database	Result
		Feature Extraction	Classification		
Taji B.et al. (2018) [27].	AFib	Deep Belief Network+ Radial Basis Network		MIT-BIH AFib Database	Gating (not applied) (at -20 dB): P Value= 25.5%, Recall= 29.3%, AC= 58.7%, Spft = 70.5% With Gating mechanism: P value= 65%, Recall: 68.1%, AC= 81%, Spft= 85%
Kadambari et al. (2018) [24].	Supraventricular Ectopic Beats Ventricular Ectopic Beats	Gaussian Bernoulli-Deep Belief Network	Support Vector Machine	MIT-BIH Supraventricular Arrhythmia Database	SVEB AC= 99.5%, VEB AC= 99.4% SVDB: SVEB AC= 97.5%, VEB: AC= 98.6%

6.4 RNN Variants

Yang et al. [28] given a model named the Global recurrent model (Table 6). GRNN shows promising results. It gives an accuracy of 99.8% in the classification of VEB and SVEB. This model has the following key features in it:
i. It has a very large capacity and fitting ability of GRNN.
ii. The model is highly scalable in terms of training and testing datasets.
iii. It has self-learning capability.

6.5 LSTM Variants

Yildirim, Ö. [29] has provided a model to classify ECG signals. This model uses low pass and high pass filters to reduce noise and layer which includes a wavelet to generate the sequence of ECG. It has taken the MIT BIH arrhythmia database and classified 5 varieties of beats namely, RBBB, LBBB, Paced Beat, PVC, and NSR with 99.39 % of accuracy. Shenfield et al. [30] model with the accuracy of 99.77% (in case of blindfold validation) and 98.51%(in case of 10-fold cross-validation) provides detection of AF beats. It uses a database of MIT-BIH AF. Table 5 shows the performance of 5 research papers. The best accuracy is 99.74 %, which is for Atrial fibrillation [54].

Table 5. Performance of Variants of LSTM

Reference	Application	Network		Database	Result
		Feature Extraction	Classification		
Zhou et al. (2019) [48]	Supraventricular Ectopic Beats Ventricular Ectopic Beats	Ventricular Premature Complexes	General Regression Neural Network	MIT-BIH Supraventricular Arrhythmia Database	MIT-BIH Database: Spft= 98.3% AC= 97.4%, Snvt=85.7%, Supraventricular Database: Spft = 99.2% AC= 97.2%, Snvt=77.2%,
Yildirim, Ö.(2018) [29]	Normal Sinus Rhythm Premature Ventricular Contraction LBBB+RBBB	Discrete Wavelet Transform	B-LSTM	MIT-BIH DB	AC=99.39%
Shenfield et al. [30]	AFib		B-LSTM	MIT-BIH DB	Snvt= 98.32%, Spft= 98.67, AC= 98.51%
Jagdeep et al. (2022)[54]	AFib, VFib	CNN	B-LSTM	MIT-BIH AF DB	AFib AC=99.71% P Value =100% F1 Score =1.0 Recall=0.99 VFib AC=99.29% P Value = 90% Recall = 92% F1 Score= 1.0

6.6 GRU Variants

Janghel et al. [31] presented three models to classify normal and arrhythmia heartbeat. In their first model, RNN has been used which shows an accuracy of 85.4% with three layers and nine iterations. In the second case, GRU has been applied which shows an accuracy of 82.5%, and lastly, LSTM provides an accuracy of 88.1 %. Table 6 shows the performance of three research papers.

Table 6. The combined performance of Variants of RNN and GRU

Reference	Application	Network		Database	Result
		Feature Extraction	Classification		
Yang et al. 2019 [28]	Supraventricular Ectopic Beats Ventricular Ectopic Beats		GRNN	MIT-BIH Database	AC= 97.4%, Snvt=:85.7%, Spft=: 98.3%
Janghel et al. (2018) [31]	Normal and Abnormal Beats	1. 3-layer Recurrent Neural Network 2. 3-layer Recurrent Neural Network -GRU 3. 3-layer Recurrent Neural Network 4. 3-layer Recurrent Neural Network -GRU 5. 3-layer Recurrent Neural Network - Long Short Term Memory		MIT-BIH Database	1. AC= 85.4%, Snvt= 80.6%, Spft= 85.7% 2. AC= 82.5%, Snvt= 78.9%, Spft=81.5% 3. AC= 85.4%, Snvt=80.6%, Spft=85.7% 4. AC=82.5%, Snvt=78.9%, Spft= 81.5% 5.AC=88.1%, Snvt=92.4%, Spft=83.35%
E. Ramaraj et al. (2021)[52]	MI	GRU	ELM	PTB-XL dataset	MI AC=88.5% Snvt=98.5% Spft=45.9% P=88.7%

7 Discussion

Here in this section first we try to juxtapose our survey paper with other surveys and provide key features of our paper. Then conceptual comparison has been given along with the applicability of Deep Learning. Finally, the complexity and limitations of DL have been provided.

7.1 Comparison with other survey papers

This paper reviewed papers that use deep learning as a classification tool or a feature extraction tool, unlike other survey papers which reviewed old technologies such Hidden Markov Model and independent component analysis (Bizopoulos et al. 2018; Dewangan et al. 2015; Dinakarrao et al., 2019; Jambukiaet al. 2015; Luz et al. 2016)[32,33,3,34,35]. Other papers like Jambukia et al. (2015) [34] reviewed papers with machine learning techniques. Dinakarrao et al. (2019)[3] presented in their paper, a survey of the classification of arrhythmia along with the performance and complexities but here in our paper, we have limited ourselves to only a deep learning model providing a narrow and focussed study with only few heart diseases.

7.2 The conceptual comparison and applicability of Deep Learning Methods:

Since our study focuses on only six important DL models and their variants. Out of them, CNN came out with the most applicable method for feature extraction. Fig. 15 shows that CNN is used as a feature extractor in 52% of research works. Atrial Fibrillation was the most contemplated disease (48%) in the reviewed research papers followed by SVEB +VEB (21%) (Fig. 16). Fig. 17 shows the models with high accuracy, models with MLP, LSTM, and CNN achieved comparatively higher accuracy in the classification tasks.

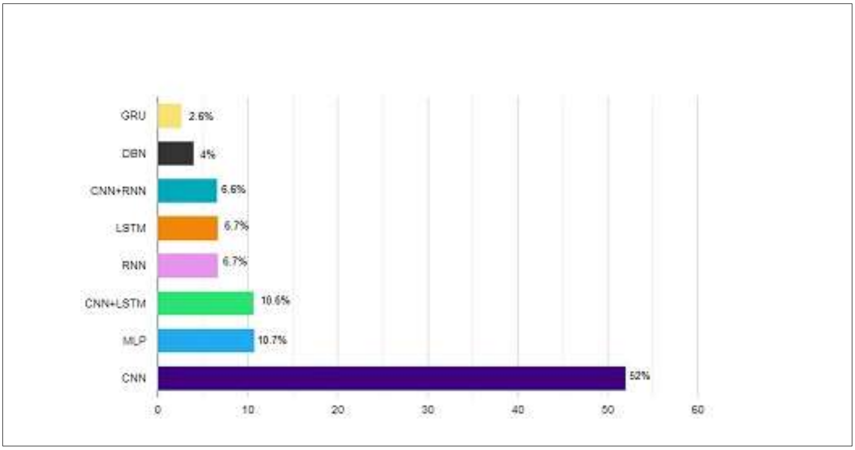

Figure 15. Participation of DL models in arrhythmia classification

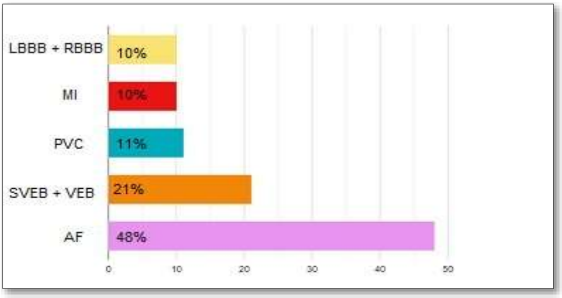

Figure 16. Percentage of major heart diseases considered during the review

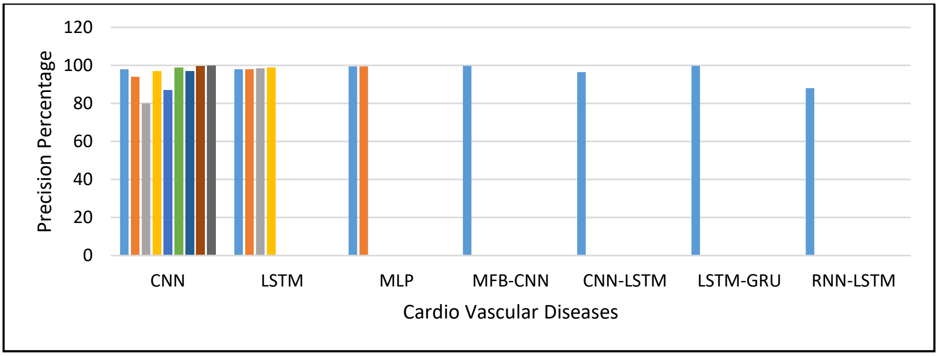

Figure 17. Higher accuracy models for classification of Arrhythmia

7.3 Limitations of the DL methods

To implement a Deep learning model following parameters should be considered: compiler optimization, the APIs (for e.g, Tensorflow / PyTorch), hardware platform, etc. There are some constraints to the DL models:

i. Deep learning models are suitable for a very large amount of test data due to this the performance may get compromised if the dataset is quite small.

ii. Deep Learning models require huge memory [5] hence they are more GPU dependent.

iii. These models also suffer from the problem of vanishing gradient.

8 Conclusions

The objective of this review paper was to study the various deep learning methods used for arrhythmia classification and to find out the most suitable method. AF, SVEB, and VEB were classified by Gated Recurrent Unit, Convolution Neural Network, and Long Short Term Memory models respectively with very high accuracy. A combination of these models may provide even better results in the classification of arrhythmia.
After the review of all specified research papers, it can be seen that CNN is the most suitable method for feature extraction (Fig. 17) and for the classification of arrhythmia. Hence working more with CNN in this area may lead to even better results.

9 Recommendations

1. Future research must consider the data of young people (aged under 35). As in India, more young people are getting affected by cardiovascular diseases.
2. More databases are required for the arrhythmia classification. As there are very limited authentic databases that can be useful for the classification of various cardiovascular diseases.

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