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Arrhythmia diagnosis of young martial arts athletes based on deep learning for smart medical care

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Abstract

Cardiovascular and cerebrovascular diseases are a serious threat to human health and increase the annual death ratio at a considerable pace. This is not uncommon even among teenagers and martial arts athletes. Due to the increased risk associated with strenuous exercise in the context of a quiescent cardiac abnormality, athletes have a higher rate of heart attack and stroke than their nonathletic colleagues. The mortality rate due to this disease is extremely high, which needs to be controlled at the initial stages. At present, the recognition and analysis of ECG signals is still an issue and requires an expert to analyse it and identify its hidden patterns. The most challenging aspect of ECG signal classification is the irregularities in the signals, which are critical for detecting patient status. Each heartbeat is made up of a variety of action impulse waveforms produced by various cardiac tissues. Classification of heartbeats is difficult because waveforms vary from person to person and are identified by certain features. At present, the automatic identification of ECG signals still requires manual design, which has low accuracy and cannot be widely used in clinical practice. This study proposes an intelligent system based on deep learning and machine learning methods to classify and diagnose ECG signals to improve their classification and recognition accuracy. It improves the detection ability of martial arts athletes' arrhythmia disease and obtains accurate arrhythmia diagnosis information. MIT-BIH arrhythmia dataset has been used for the experimental analysis. The performance of the proposed scheme is evaluated with the help of various performance measures. We conduct comprehensive experiments, and the results show that the algorithms used in this paper are robust.

Keywords Arrhythmia Diagnosis · Smart Medical Care · Deep Learning · Young Martial Arts Athletes · Neural Network

1 Introduction

Arrhythmia is a serious issue that occurs as a result of the unusual behavior of heartbeats or rhythm. The heartbeat may be very fast, very slow, or in an irregular rhythm during an arrhythmia [1]. When the heart beats slowly compared to normal beats, then a specific condition known as bradycardia occurs. When the heart beats very fast compared to the normal beats, the result is tachycardia [2]. Changes in heart tissues and activities and changes in the electrical signals that control the heartbeat can cause arrhythmia. The changes in heartbeats are caused by various diseases, injuries, and genetics as well. Although, there are no symptoms, but sometimes people feel dizzy, faint and have difficulty breathing due to irregular heartbeat [3, 4].

An electrocardiogram (EKG or ECG) is the most common and widely used testing method for identifying and diagnosing arrhythmia [5, 6]. A practitioner may perform other required tests as well if needed. The patient may be advised proper medications, placement of diagnostic devices that can help monitor and control heartbeats, or even surgery to repair the nerves that result in the overstimulation of the heart. If this disease is ignored, the heart may fail in pumping a sufficient amount of blood to all body parts. It can harm the heart, brain, or other body parts of a human being. Hence, identification/diagnosis of this disease at the early stages is crucial to help the athlete continue his/her career.

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Table 1 Confusion matrix

	Predicted (Normal)	Predicted (Abnormal)
Actual (Normal)	TN	FP
Actual (Abnormal)	FN	TP

The number of affected people due to cardiovascular disease increases with time. Approximately 15 million people die due to this disease each year, and it becomes the leading cause of mortality compared to other diseases [7]. In recent years, the number of patients suffering from cardiovascular diseases has increased at a much higher pace, leading to regional imbalances worldwide [8]. Cardiovascular and cerebrovascular diseases are a severe threat to human health, which leads to life insecurity. These diseases are common among martial arts athletes as well [9]. To diagnose the cardiovascular diseases of martial arts athletes, ECG signal is used by the physician and is considered the primary method for identifying these diseases. ECG signals reflect the real-time conditions of the human heart and contain extensive and essential information of every activity of the heart. Cardiovascular diseases are diagnosed mainly by identifying the width, amplitude, period, waveform, and relationship of each wave in the ECG signal [10]. Among these, the width, amplitude, and period of the wave can be measured from the electrocardiogram patterns. Still, there is no precise measurement of the wave shape and the relationship between the waves. The electrocardiogram is an important technique for diagnosing heart diseases and is more valuable, especially in diagnosing and analyzing various arrhythmias and conduction obstacles [11]. This technique has a great diagnostic value and is the most accurate method to identify various arrhythmias. The heart activities can be observed from the electrocardiogram, which has been widely used in clinical practices [12]. Therefore, it is of great significance to study the diagnostic technology based on the automatic analysis of ECG signals to improve the efficiency and accuracy of the diagnosis of martial arts athletes.

The conventional techniques used to analyse the electrocardiogram of the martial art athletes were mainly based on the physician's naked eye observation. The analysis results were based on the physician's expertise in the desired field and the existing theoretical knowledge. For complex cases, the doctor may need to call a meeting of experts to obtain accurate results [13, 14]. Further, a relatively smaller amount of medical resources are required to diagnose arrhythmia through an electrocardiogram, which makes the importance of the earlier approaches less significant. The second biggest problem associated with the earlier approach was that there is a financial crisis nowadays, and every country is facing it. The third problem associated with the conventional technique is that an expert cardiologist needs a precise test to diagnose an athlete's heart conditions as human medical resources are scarce. Moreover, long-term manual diagnosis may reduce the doctors' efficiency and affect the accuracy of the final diagnosis.

In addition, the artificial recognition of the ECG signals has a lag. It cannot be monitored in real-time, which will seriously affect the patient's condition and disease prediction. Therefore, to solve the above problems, using the advantages of deep learning to automatically extract features and classification, we use deep learning methods to classify and recognize ECG signals, improve the detection ability of arrhythmia diseases, and obtain accurate arrhythmia diagnosis information. Following are the main contributions of our work.

- This paper proposes a novel deep neural network method to classify and diagnose ECG signals and improve the detection ability of arrhythmia diseases.
- The performance of ECG classification i.e., arrhythmia diagnosis has been tested with the help of various machine learning algorithms.
- The existing method to solve the imbalance of ECG categories is usually to put the missing categories into the training model multiple times to balance the training set categories. However, because of the small amount of data, the amount of information provided to the training model does not change. After the iteration, the depth features cannot be effectively mapped to the high-dimensional space. The rare class often appears as an over-fitting state, resulting in a low generalization ability of the rare class. Once the data are mixed with noise, it is difficult to recognize, and the recognition ability of arrhythmia is also relatively in view of the above problems, this paper proposes a GAN-based recognition method. This method uses the CNN model to verify, find the under-represented categories and under-represented sample data. The rare class and under-represented samples are input into GAN according to the rules to train the generator and discriminator for multiple iterations, and then use the generator to generate new data, and the discriminator to filter the data to increase the corresponding data volume and combine them into a new and balanced training set.
- The effectiveness and superiority of the proposed model has been proved with the help of various experiments and simulation results.

The rest of the paper is arranged in the following order: Sect. 2 represents the related work, Sect. 3 illustrates the methodology, and Sect. 4 notifies the experimental analysis and results. In Sect. 5, we conclude our research work.

2 Related work

The ECG signals are very susceptible to external interference and noise and the presence of both of the phenomenon affects the classification accuracy [15] of these ECG signals. In order to take rid of both of the phenomenon, various preprocessing techniques have been used in the past and still are in active state. The main theme of ECG signal preprocessing is to filter out the noise in the signal, provide high-quality ECG signal, and to obtain diagnostic information of arrhythmia disease. Rahman et al. [16] have used an adaptive filter based on time–frequency domain to filter out ECG signals and to remove noise from it. Their proposed method performed well and can effectively filter out the noise in ECG signals. Sundara raj et al. [17] proposed an effective scheme for the diagnosis of ECG signals that using wavelet threshold mechanism, based on the anti-adaptive learning particle swarm optimization in dual-tree complex wavelet packet scheme. Their proposed scheme showed good visual quality but its performance degrades as the amount of data increases. Chiang et al. [18] proposed a method of diagnosing ECG signals using DAE of fully connected Convolutional Neural Network. At the same time, the proposed FCN-based DAE can perform compression related to the DAE architecture.

Feature extraction of ECG signals is an important step in order to extract useful features from the ECG signals and to present those features to the models. The models will then further process these features and will track the health conditions of patient. The extraction of important features improves the performance of classification and recognition of ECG signals. The quality of the extracted features will affect the accuracy of ECG signal classification and recognition. The process of manual feature extraction is complicated and cumbersome, with low efficiency, and it is difficult to effectively extract high-quality features. Feature extraction is mainly to extract morphological features, time interval features, high-order statistical features, wavelet transform features, etc. [19–21].

The advancement of machine learning (ML) and deep learning (DL) techniques have bring a huge revolution in the modern era and has been extensively used in various fields. In the past couple of years, DL has been widely used for the classification of ECG and EEG signals. For example, Nurmaini et al. [22] have used convolutional neural network (CNN) to identify the type of arrhythmia. The simulation result shows that the performance of his proposed method was good in terms of accuracy and performed well in the classification of ECG signals. Lu P et al. [23] have used deep belief network (DBN) for the automatic extraction of features from EEG signals data, independently determine the network depth, and obtained good classification accuracy. Murugesan et al. [24] proposed a new deep learning architecture based on the combination of CNN and LSTM for the identification and classification of ECG signals. Their proposed architecture showed good performance in terms of accuracy. In another study, Peimankar et al. [25] proposed a new algorithm (DENS-ECG) that combines the CNN with LSTM to detect onset, peak, and offset of different heartbeats waveforms such as P-waves, QRS complexes, T-waves, and No-waves (NW). Their proposed model takes ECG signals [26–28] as input; model learns to extract high level features through the training process, which unlike the other classical machine learning-based methods, eliminates the feature engineering step. By increasing the number of hidden layers, the feature extraction ability is improved, but the number of parameters and calculation time of the network increase, and the network operation become extremely time-consuming.

Li et al. [29] have proposed a technique based on multi domain feature extractor along with wavelet threshold for the identification of arrhythmia and attained promising results. Rajagopalan et al. [30] developed a new algorithm that categorizes ECG signal quality into five levels: clean, minimal noise, medium noise, serious noise, and intense noise. Further, to classify the quality of the ECG signals the algorithm utilizes a machine learning approach which is a significant contribution to their algorithm. In another study, Zhang et al. [31] proposed a system that reduces the noise present in ECG signals. Their proposed system was basically a combination of discrete wavelet transformation and empirical Bayesian posterior median wavelet shrinkage technique. The absence of performance metrics assessment, which is an indication of the established method's efficacy, is a major limitation in this study. Eminaga et al. [32] have developed a framework to filter out the noises from the ECG signals with the help of wavelet, Bayesian, and band pass filter. The effect of the various wavelet techniques used for noise reduction is not explored in this study, which is a limitation. Balaskas et al. [33] have proposed a framework to analyse the ECG signals via discrete wavelet transformation and artificial neural network.

3 Methodology

This section represents the material and techniques used in the accomplishment of this research work.

3.1 Dataset

The training and development of an intelligent system/model depends extensively on the dataset that imitate the pattern of the target class and is more related to the problem. Problem-specific and well-organized dataset has a great influence on the efficiency of an intelligent and automated model. In order to keep the importance of the dataset in consideration, this study uses the MIT-BIH arrhythmia dataset for all the experimental and simulation work. Complete information and description of the utilized dataset is available in [34].

3.2 Proposed system methodology

The key objective of the proposed system is to diagnose the health conditions of young martial arts athletes through their ECG signals. MIT-BIH ECG dataset has been used in this study. Several preprocessing methods are investigated to provide the data in a normalized form to the classification models. The dataset is divided into two main parts i.e., training and testing. In this study, 70% of the data is used for training while the rest of the 30% is used for testing and validation purposes. In this study, two distant deep learning (DL) algorithms namely: Generative adversarial network (GAN) and artificial neural network (ANN), and two important and extensively used machine learning (ML) algorithms i.e., support vector machine (SVM) and Logistic Regression (LR) are used for the classification of ECG signals of young martial arts athletes. The models are trained on 70% of the data, after training the models the testing data are presented to the trained models which then classify the health conditions that whether the ECG data of the martial arts athlete is normal or abnormal. Various performance measures are used to assess the efficiency of the utilized models. Figure 1 shows the graphical representation of the proposed methodology.

3.3 Data preprocessing

Data preprocessing is an important technique used to represent the data in an organized and normalize manner to the classification models. In this study, two preprocessing methods namely, MinMax scaler and standard scaler are used to make the dataset more efficient for the classification. The use of these techniques significantly improves the performance of the models.

3.4 Utilized DL and ML models

In this study, two DL and two ML algorithms are investigated for the classification of ECG signals of martial art athletes. The significance and importance of each algorithm is based on the nature of the problem and its applications are highly dependent on the problem. The use of multiple algorithms helps in the recognition and selection of a generalized predictive model. Below is a brief description of the utilized ML and DL classification models.

3.4.1 Support vector machine (SVM)

SVM is a trustworthy classification technique that partitions instances into two groups by defining a hyperplane that determines the differentiation margin between them. SVM was developed with the aim of producing high-performing applications. In order to deal all the instances of a given database, it uses the formula $\{(x_1, y_1)\ldots, (x_n, y_n)\}$. Here y_i demonstrates that each input point X_i belongs to

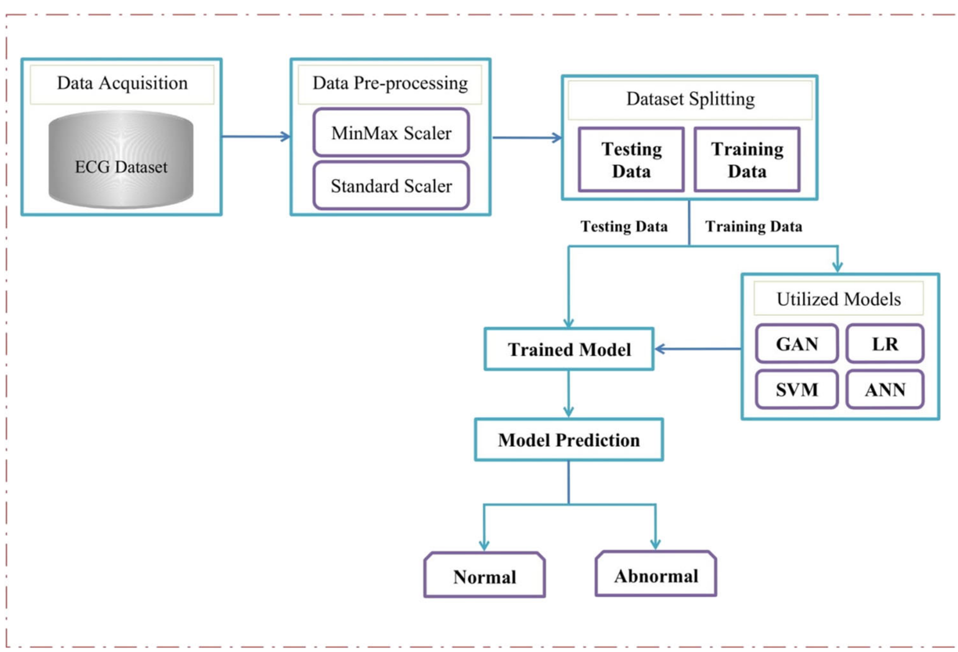


Fig. 1 Methodology of the proposed system

which class. The hyperplane can be drawn between the input points using the below formula:

$$W.X_i + b = 0 \tag{1}$$

In order to identify the best hyperplane which separates the input point values into two categories can be described as $Y_i = \pm 1$. The gap between the input points and the hyperplane is when high the classification results is high and is considered to be the best and ideal conditions. The hyperplane having the maximum margin space can be formulated as follow:

$$W.X_i + b = \pm 1 \tag{2}$$

While the distance between the data point and a hyperplane can be computed as follows:

$$d = \frac{|W.\mathrm{Xi} + b|}{||w||} \tag{3}$$

In Eq. 3, if the value of the numerator is put as 1 then according to Eq. 2, the gap between the support vectors and the hyperplane can be computed as follows:

$$d_{\text{support vector}} = \frac{1}{w} \tag{4}$$

3.4.2 Artificial neural network (ANN)

ANN is one of the important and widely used classification algorithms, inspired from the concept and functionality of human brain. It comes under the category of nonlinear modeling techniques, particularly used to solve the complex problems and to carry out the relationship among the inputs and output. It comprises of various layers i.e., input, hidden, and output layers that are interconnected with each other. Every layer consists of one or more nodes, and the function of each layer is different. Following are some of the simple steps that describe the working of ANN.

- The input layer is used to get the data from outside and forward it to the hidden layers.
- Connection among layers carries weights on each line that connect the layers with each other.
- The weights are multiplied with the inputs, and then a bias value is added to it.
- Compute the weighted sum of the weights, inputs, and bias value and pass it through the activation function.
- The activation function produces a result, which is considered as the output value.
- In order to reduce the error, back propagation technique comes into play, and the weights are adjusted accordingly.
- The output of one layer is used as input for the other layer.

ANN is best to deal with complex problems that are much easier for it as every layer work almost both as input and output layer. The inner layers of an ANN try as much as possible to learn about the data collected from the previous layers by adjusting the weights according to the target value. These techniques allow nodes to yield a transformed output values, which is then passed to the other layer which takes it as input value and so on. Back propagation also play its part in adjusting the weight and learning rates in order to reduce the error rate and improve the classification results.

3.4.3 Logistic regression (LR)

LR is among the most commonly used ML classification algorithm. LR remains the first choice for the researchers and programmers to deal with the binary classification problems. In case of binary problems, the prediction value of LR lies in the domain of $y = [0, 1]$, where y is a variable that represents the target class value. The target value 0 is treated as negative class while 1 represents the positive class. Further, 0 represents that the person is healthy while 1 demonstrates a patient whose ECG signals are above normal range i.e., abnormal case. LR can also be used to deal with problems consists of multi-class problems in order to forecast the rate of the forecaster variable y where $y = [L1, L2, L3, L4]$ where L represents the label of the target class. For instance, a hypothesis $h(Q) = Q_t{*}X$ is supposed to categorize the two class problem, and the target threshold value of the classification model is $h_Q(X)$ at 0.50. When the output value of the hypotheses cross the above-mentioned threshold value i.e., 0.50 then it gives the output $y = 1$, which shows that the athlete ECG signals are above the normal range and has arrhythmia. When the hypothesis gives the output as $y = 0$, then it means that the martial art athlete is healthy and does not have arrhythmia. LR is mostly used in the disease prediction applications and other stuffs, and also used for other purposes such as forecasting, marketing, agriculture, etc. LR can be described mathematically via the following equation.

$$Y = \alpha 0 + \alpha 1x1 + \alpha 2x2 + \cdots, \ \alpha n\mathrm{Xn} \tag{5}$$

3.4.4 Generative adversarial networks

Generative Adversarial Neural Network (GAN) was proposed by Ian Goodfellow in 2014. GAN is composed of two relatively independent networks: Generator and Discriminator. In terms of these two parts, the GAN model has two different goals. The generator is to generate data, and the discriminator is for classification and discrimination. Although GAN does not require manually labeled tags, there are still tags in the discriminator. The original data are regarded as a true sample, and the generator generated is regarded as a false sample. The goal of the discriminator is to distinguish true and false samples. The generator aims to generate data that the discriminator cannot discriminate, while the discriminator aims to better recognize the generated data. Through the mutual game between the generator and the discriminator, the generator and the discriminator are both trained and optimized. Finally, a generator model that can generate fakes and a discriminator that can identify authenticity to the greatest extent is obtained. The structure of the generated adversarial neural network is shown in Fig. 2.

The generator aims to generate data close to real data. Usually a random vector with the same dimension as the original data (extracted from a normal distribution) is used as input, and the multi-layer perceptron, convolutional neural network, auto-encoder and other methods are used to make the input random vector fill the sample space. Then through the game with the discriminator, the objective function is continuously optimized to maximize the likelihood. In the GAN model used in this article, a convolutional neural network is used to perform deconvolution operations to complete vector up sampling. The likelihood of the generated model is calculated as follows:

$$L = \prod_{i=1}^{m} P_G(x^i;\ \theta) \tag{6}$$

We want to maximize this likelihood, which is equivalent to letting the generator generate those ECGs with the greatest probability, so we need to find a θ^* to maximize this likelihood.

$$\begin{aligned}\theta^* &= \arg\max_{\theta} \prod_{i=1}^{m} P_G(x^i;\ \theta) \\ &= \arg\max_{\theta} \log \prod_{i=1}^{m} P_G(x^i;\ \theta) \\ &= \arg\max_{\theta} \sum_{i=1}^{m} \log P_G(x^i;\ \theta) \\ &\approx \arg\max_{\theta} E_x \sim P_{\text{data}}[\log P_G(x^i;\ \theta)] \\ &= \arg\max_{\theta} \int_x P_{\text{data}}(x) \log \frac{P_{\text{data}}(x)}{P_G(x^i;\ \theta)} dx \\ &= \arg\max_{\theta} \text{KL}(P_{\text{data}}(x) || P_G(x;\ \theta))\end{aligned} \tag{7}$$

The discriminator is mainly to identify true and false samples, similar to the classification model. Because the generated adversarial neural network model is often used in the image field, the discriminator is usually the main body of the convolutional neural network. For example, the discriminator in the GAN model used in this article is a CNN model composed of 3 layers of convolutional layers, 2 layers of pooling layers, and 1 layer of fully connected layers. The calculation equation of GAN is as follows:

$$\begin{aligned}\min_G \max_D V(D,\ G) = E_x \sim P_{\text{data}}(x)[\log D(x)] \\ + E_z \sim P_z(z)[\log(1 - D(G(z)))]\end{aligned} \tag{8}$$

3.4.4.1 CNN-GAN arrhythmia recognition This study also improves the VGG16 mode and designs a one-dimensional CNN heart rhythm recognition model. The VGG16 model is also known as VGGNet and was jointly proposed by the Visual Geometry Group of the University of Oxford and

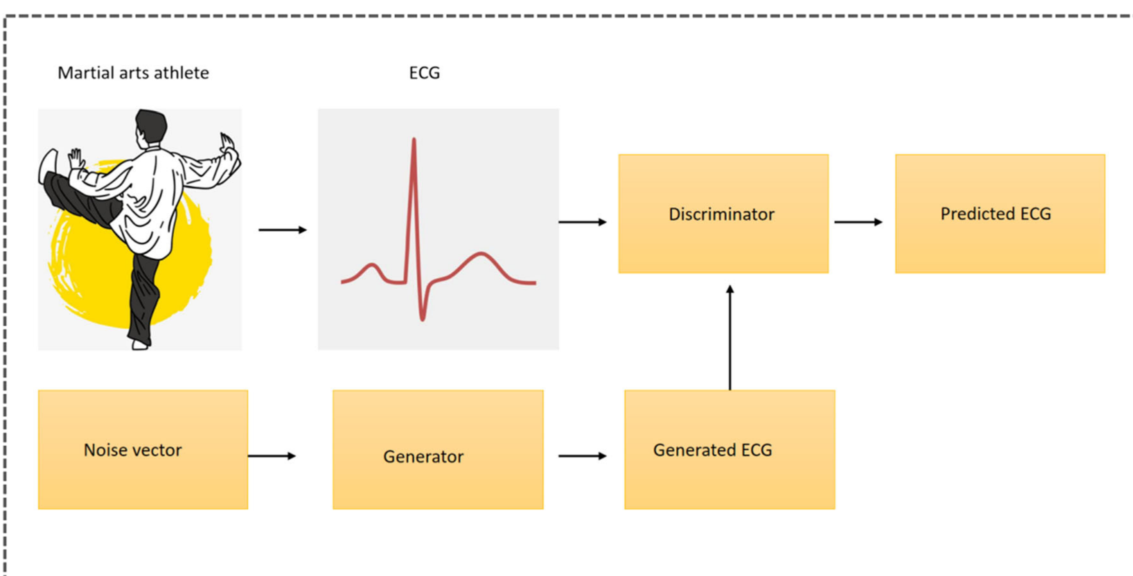


Fig. 2 Generative adversarial neural network

researchers from Google DeepMind. In the ILSVRC-2014 competition, they achieved outstanding results in positioning tasks and second in classification tasks. VGG16 explored the relationship between the depth of the convolutional neural network and its performance. By repeatedly stacking a 3×3 small convolution kernel and a 2×2 maximum pooling layer, it showed its excellent feature extraction ability, and it was more effective than others. The generalization ability of the dataset is also outstanding. To this day, VGG16 is still widely used to extract image features. This article explores how to generate effective ECG data, thereby reducing data imbalance. In the early stage of the research, referring to the idea of adversarial samples small number of sampling points in the ECG signal was removed, and then the corresponding sampling points were smoothed and supplemented by smoothing filtering, so as to generate corresponding types of expanded data. However, experiments show that this method has two drawbacks. First, the ECG expanded data generated is too similar to the original ECG data, and the amount of information carried is basically the same, and the heart rhythm recognition model cannot better extract features from it; secondly, in a single ECG the amount of signal data is not that huge. There is a high probability that the peak of the ECG signal will be removed when the sampling point of the ECG signal is removed. After the peak is removed, the smoothing filter will destroy the ECG signal, and the QRS wave in the ECG. The peak tip is its key feature. Although, the overall recognition ability of the model has not been greatly improved due to the above drawbacks, it reduces the tendency of model fit to larger data volume. In order to avoid the above-mentioned drawbacks of the generated extended data, by analyzing the characteristics of the ECG data and the GAN model, this paper proposes a method of selecting rare data and error-prone data from the CNN recognition model, and then using the generator of the DCGAN model to generate the extended data.

3.5 Performance measures

The last step after preprocessing and classification is to check the efficiency of the models in terms of various performance evaluation metrics that assists in tracking the performance of the model. In this study, the most common and important performance measures namely; accuracy, sensitivity, specificity, AUC, and recall are computed with the help of confusion matrix. Another important performance measure, ROC curve is used to measure the performance of the proposed system graphically. All the performance metrics are calculated by using the confusion matrix as shown inTable1.

Following are the formulas through which these measures are computed:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} * 100 \tag{9}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} * 100 \tag{10}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} * 100 \tag{11}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} * 100 \tag{12}$$

$$\text{MCC} = \frac{\text{TP} * \text{TN} - \text{FP} * \text{FN}}{\sqrt{(\text{TP} + \text{FP})(\text{TP} + \text{FN})(\text{TN} + \text{FP})(\text{TN} + \text{FN})}} \tag{13}$$

4 Experimental analysis and results

This section represents the experimental analysis and simulation results attained via the 4 utilized DL and ML classification algorithms i.e., SVM, ANN, LR, and GAN. All the simulations were carried out using the MIT-BIH ECG dataset. The performance of the utilized deep learning and machine learning models was checked on the MIT-BIH ECG dataset. The dataset is divided into two parts i.e., training and testing, where 70% of data is used to train the models while the remaining 30% is used for the testing and validation purpose. In addition, preprocessing methods are used to represent the data in a normalized form to the utilized ML and DL classification models. Indeed performance metrics play an important role in tracking the performance of the models. To measure the performance of the ML and DL models, different performance metrics were used.

All the experiments were performed using Python 3.7, anaconda Jupyter Notebook environment on Microsoft Windows10. The system specifications include Intel core-i5 7^{th} generation, (3.30 GHz) processor with the main memory (RAM) of 16 GB. The main libraries and packages used in carrying out this study include; Scikit-learn, numpy, matplotlib, seaborn, Keras, TensorFlow, etc.

4.1 Experimental outcomes of all the utilized DL and ML classification models

This subsection represents the experimental outcomes of all the utilized four DL and ML classification algorithms i.e., two ML algorithms (SVM and LR) and two DL algorithms (ANN and GAN). The simulation results attained via these models are shown in Table 2.

Table 2 Experimental outcomes of the utilized classification models

Model	Accuracy	Sensitivity	Specificity	AUC	Precision	Recall	f1-measure	MCC
GAN	97.02	94.74	98.50	98.30	98.44	94.74	0.97	0.93
ANN	96.10	93.58	98.61	97.85	98.54	93.58	0.96	0.92
SVM	94.59	95.43	93.75	95.90	93.86	95.43	0.95	0.89
LR	87.01	86.36	87.33	88.00	88.71	86.36	0.88	0.74

From Table 2, it is obvious that Generative Adversarial Neural Network (GAN) performed extremely well in terms of all performance measures as compare to the rest of the models and stood first in the performance competition. GAN achieved the classification accuracy of 97.02%, sensitivity of 94.74%, specificity of 98.50%, AUC-score of 98.30%, precision of 98.44%, recall of 94.74%, f1-measure of 0.97, and MCC of 0.93. ANN stood second in this competition and attained the accuracy of 96.10%, 93.58% of sensitivity, 98.61% of specificity, 97.85% of AUC-score, 98.54% of precision value, recall of 93.58%, f1-measure of 0.96, and MCC-score of 0.92. For the SVM classification model, we perform two experiments one is for 'linear' kernel and the other one for the 'rbf' kernel. The best performance was observed for the SVM (kernel = 'rbf') and achieved the classification accuracy of 94.59%, sensitivity of 95.43%, specificity of 93.75%, AUC-score of 95.90%, precision value of 93.86%, recall value of 95.43%, f1-score of 0.95, and MCC-score of 0.89. Consequently, the lowest performance was observed for the Logistic Regression (LR) model and attained the classification accuracy of 87.01%, specificity of 87.33%, sensitivity of 86.36%, AUC-score of 88.0%, precision of 88.71%, recall of 86.36%, f1-measure of 0.88, and MCC value of 0.74.

After empirically assessing all the utilized models success rates, it was reported that the GAN classification model outperformed all the other models used in this study in terms of all performance measures. LR, on the other hand, performed poorly in terms of all performance as compared to the rest of the models.

Figure 3 shows the performance (accuracy, sensitivity, and specificity) of all the classification models used in this study.

From Fig. 3, it is quite clear that GAN again beats all the models used in this study in terms of the mentioned performance metrics (accuracy, sensitivity, and specificity). ANN stood second in the performance race while LR performed poorly and was ranked the last classification model in the performance competition. Figure 4 demonstrates the precision, recall, and AUC-score of all the classification models used in this study.

Again from Fig. 4, it is reported that GAN performed really well in terms of the mentioned performance measures and stood first in the performance competition. The lowest performance in terms of these measures was observed for LR and stood last in this regard.

The f1-measure and MCC-core of the utilized four machine learning and deep learning classification models are illustrated in Fig. 5.

Indeed ROC curve is also an important performance measure that helps in the assessment of the model performance. Figure 6a shows the individual ROC curve of GAN model while Fig. 6b shows the individual ROC curves of the ANN classification model.

Figure 7a shows the individual ROC curve of SVM model while Fig. 6b shows the individual ROC curves of the LR classification model.

Figure 8 illustrates the ROC curves of all the utilized classification models together. From Fig. 8, it can be noted that again the GAN model performed extremely well and attained the first spot in this competition as well.

Machine learning and deep learning methods and algorithms are playing an increasingly important role in the healthcare nowadays, helping to accurately diagnose and predict a wide range of disease. The process of getting diagnosed and identifying different diseases has vastly improved due to these machine learning and deep learning techniques. In this study, we have used two deep learning and two machine learning algorithms for the diagnosis of arrhythmia disease in young martial arts athletes. From the simulation and experimental results, it is reported that the most significant and vital DL model for the diagnosis of arrhythmia disease in young martial arts athletes is generative adversarial neural network. The second best performance was observed for artificial neural network. Logistic regression showed comparatively poor performance in the diagnosis of arrhythmia disease of young martial arts athletes. Our proposed system is anticipated to be of a great help for the doctors in order to diagnose the desired disease in the young martial arts athletes in and efficient and effective manner.

5 Conclusion

Identifying the health conditions of an athlete is an important and crucial task, which helps the athlete continue his/his career for a longer time and save them from impairment and loss. The damage caused by this disease

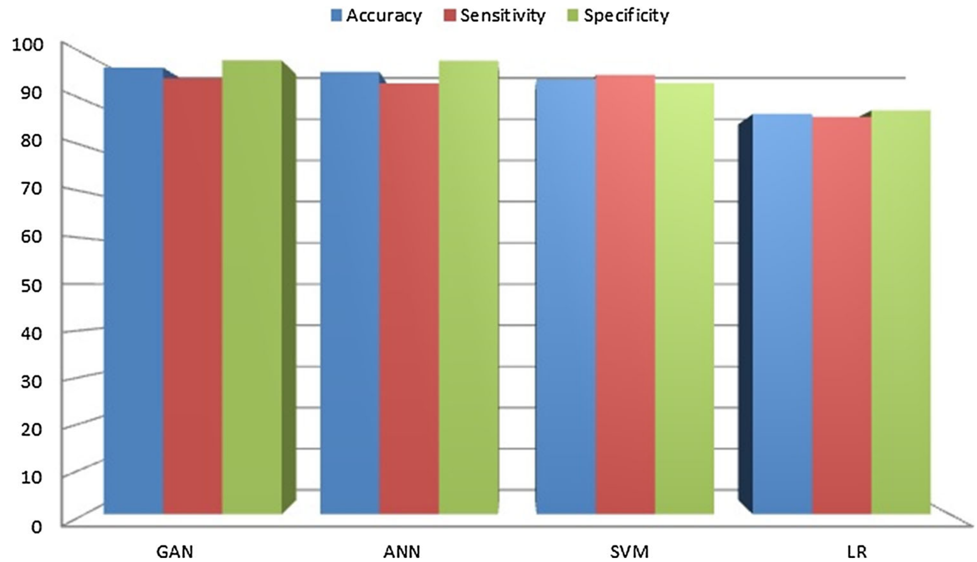


Fig. 3 Performance (accuracy, sensitivity, specificity) of the utilized classification models

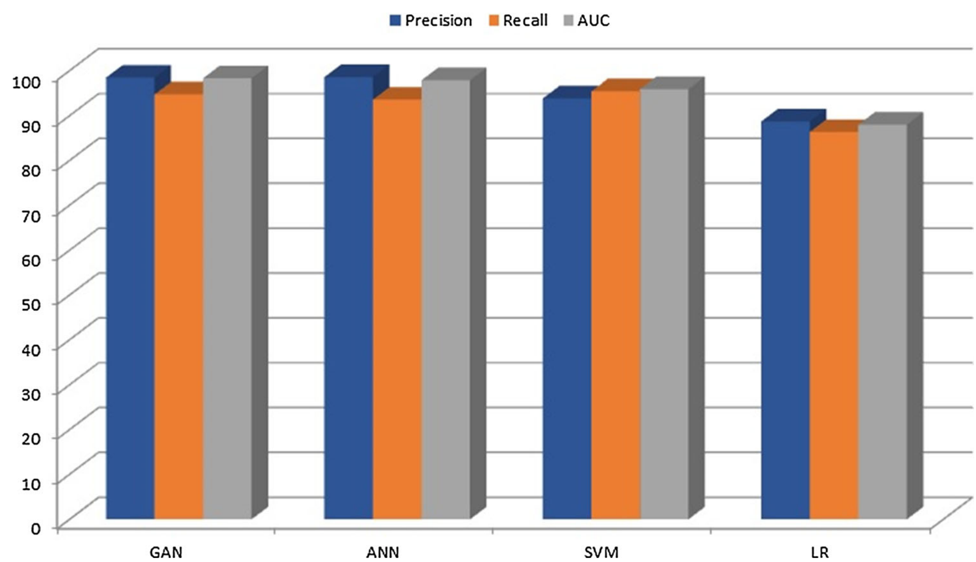


Fig. 4 Precision, Recall, and AUC-score of the utilized classification models

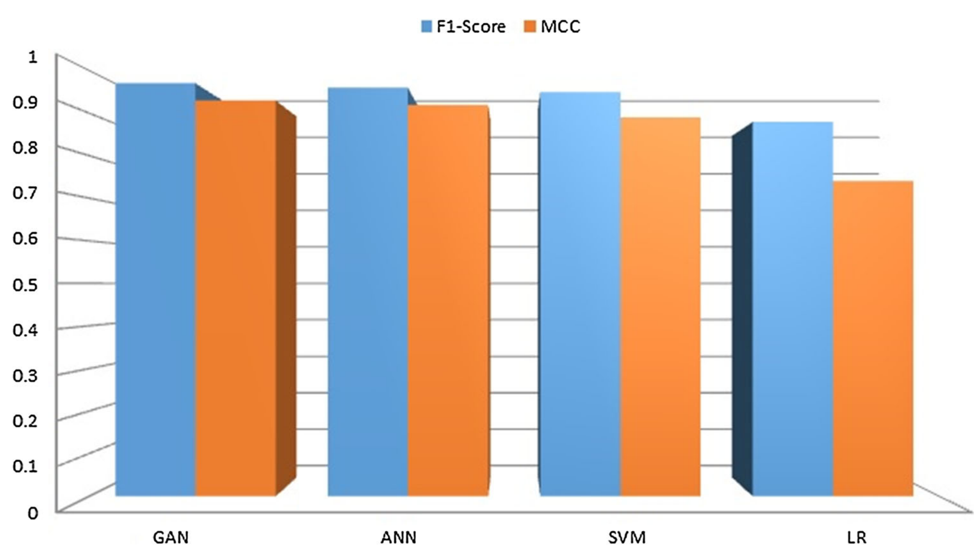
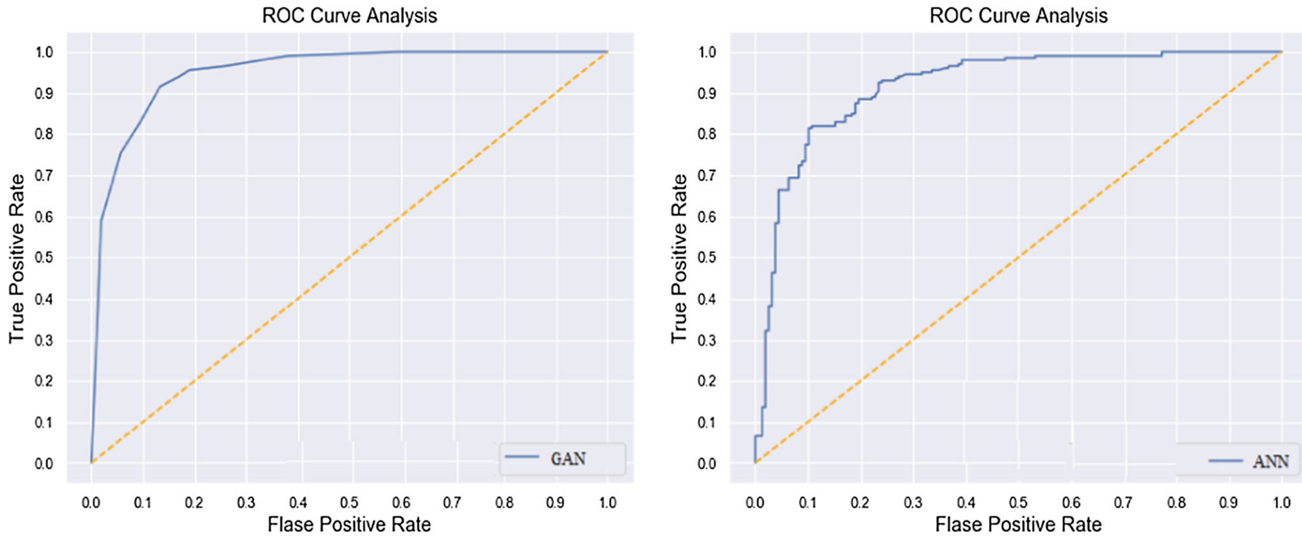
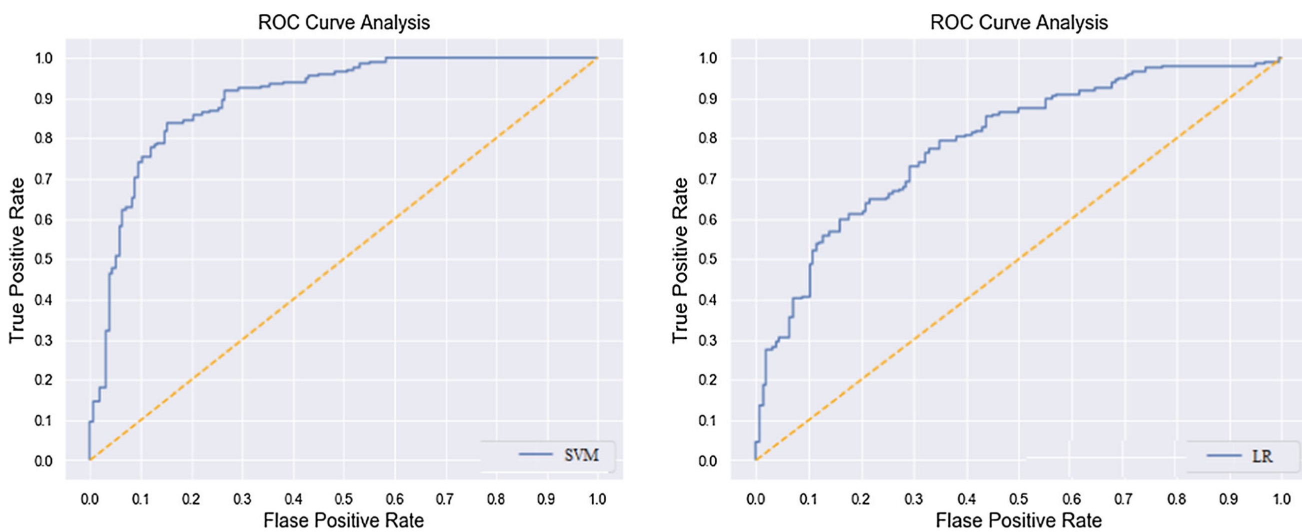


Fig. 5 f1-measure and MCC-score of the utilized classification models



(a) GAN **(b)** ANN

Fig. 6 ROC curves of GAN and ANN classification models



(a) SVM **(b)** LR

Fig. 7 ROC curves of SVM and LR classification model

can be reduced significantly if the athletes are diagnosed at early stages, and proper medications are provided to them. In this study, an intelligent predictive system is proposed based on ML and DL classification models for the arrhythmia diagnosis of young martial arts athletes. The proposed system was trained and tested on the MIT-BIH arrhythmia dataset. In this study, two ML (SVM and LR) and two DL (ANN and GAN) classification models were used to identify arrhythmia disease in young martial arts athletes. To track the performance of the utilized ML and DL models, various performance measures have been used. Experimental results show that the DL algorithm used in this study improves the ability of martial arts athletes to detect arrhythmia and obtain accurate arrhythmia diagnosis information. DL model (GAN) performed excellently and attained an accuracy of 97.02%, a sensitivity of 94.74%, and a specificity of 98.50%. It is anticipated that this system will assist doctors in diagnosing the arrhythmia of young martial arts athletes. It can be used for real-time ECG detection to assist doctors in diagnosing and analyzing arrhythmia, which has important practical significance. In future, we aim to improve the performance of the predictive system for the diagnosis of arrhythmia in young martial arts athletes by incorporating more optimization methods and classification algorithms.

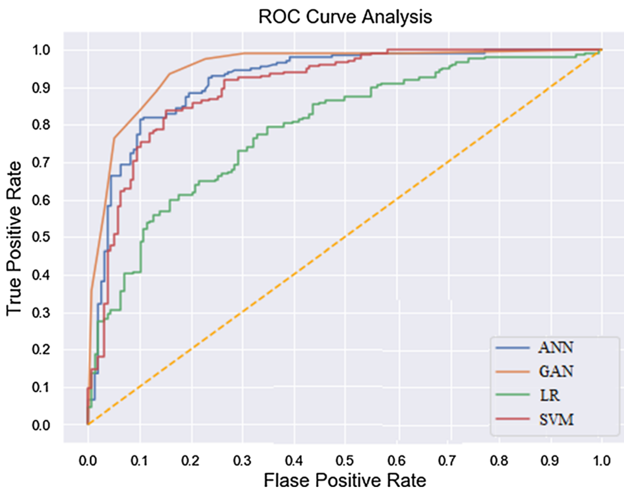


Fig. 8 ROC curves of all the utilized classification models

Declarations

Conflicts of interest The authors declare no conflict of interest.

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