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Inception based GAN for ECG arrhythmia classification

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Abstract

Cardiovascular diseases are the world's principal reason for death, accounting it about 17.9 million people per year, as reported by World Health Organization(WHO). Arrhythmia is often a heart disease that is interpreted by a variation in the linearity of the heartbeat. The goal of this study would be to develop a new deep learning technique to accurately interpret arrhythmia utilizing a one-second segment. This paper introduces a novel method for automatic GAN-based arrhythmia classification. The input ECG signal is derived from the fusion of well known Physionet dataset from MIT-BIH and some Hospital ECG databases. The ECG segment over time is used to detect 15 different classes of arrhythmias. The GAN network uses an attention-based generator to learn local essential features and to maintain data integrity for both time and frequency domains. Among these, the highest accuracy obtained is 98%. It can be inferred from the results that the proposed approach is smart enough to make meaningful predictions and produces excellent performance on the related metrics.

Keywords: Electrocardiogram, ECG classification, Inception, GAN, Generative adversarial network

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1. Introduction

Cardiovascular diseases is the world's principal reason for death, account it about 17.9 million people per year, as reported by World Health Organization(WHO)[**?**]. All of these can be greatly reduced in primary healthcare facilities by recognizing those who are at the high risks of Cardiovascular diseases (CVDs) and ensuring that they receive appropriate treatment. In the medical care, electrocardiogram is the diagnosed by beat-by-beat but this process is usually time-consuming and laborious. Obviously, these reading is not comfortable for untrained eyes. In reality, it might even be subjective, sometimes leading to different interpretations from several cardiologists.

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Electrocardiography is the process of monitoring and diagnosing the abnormalities present in cardiac, functional disorders and cardiac arrhythmias. An ECG signal consists of a series of heartbeats (or called waves) that repeat periodically in time and represents the electrical activity of the heart over time. A major reason for the need of precise ECG interpretation is the consideration that the tracing of the ECG segment is very important for the assessment of an individual's health.

The paper is organised as follows: Section **??** describe the background for ECG arrhythmia and well known state of the art methods are briefly explained. Methodology along with own contribution is presented and implemented in section **??**, Experimental result and its comparison with other well known methods is done in section **??**. Section **??** conclude the proposed method and its outcome.

2. Literature review

In past few decades, there seems to be a considerable rise in advancement in ECG signal processing in the application such as automatic detection of different cardiac arrhythmias suggesting different machine learning and deep learning technique. This methods, however, had such a range of drawbacks, particularly computational complexity throughout the training process, that directly affect the ability to adapt to personalized healthcare systems. Those system needs large memory for real time execution.

B.Mathunjwa et.al [**?**] proposed two stage deep neural network to classify six types of classes. They convert Two-second ECG 1D segments into RPs of 2D segments to increase the reliability of their system. Then R-peak detection algorithm is used on RPs. Their algorithm is unable to achieve superior discrimination on long-duration ECG segments. F. Dias et.al [**?**] uses feature level fusion of RR intervals, signal morphology, and higher-order statistics. These features were classified using a linear discriminate classifier in to 5 classes. Ferretti J.et.al [**?**] suggest one dimensional CNN for classification of ECG arrhythmia. Mohapatra K.et.al [**?**] classified four types of long duration arrhythmia electrocardiograms from MIT-BIH arrhythmia database using convolutional neural network. Empirical mode decomposition and their average power and coefficient of dispersion are is used for feature extraction.

S. Sakib et.al [**?**] proposed a deep-learning, lightweight arrhythmia classification system that used a modified one-dimensional convolutional neural network. Rashed M et.al. [**?**] implemented a classification of ECG beat based on CNN using VGG16-which uses time-frequency approximation of the temporal ECG. This technique is capable of identifying the contribution of interpretable ECG frequencies while categorizing on the basis of SHapley Additive exPlanation values. Pandey et.al [**?**] proposed deep convolutional encoding based on non-linear compression composition is used to reduce the size of the ECG segment. Convolutional encoder-based long-term memory network classification model is used to predict arrhythmias from the ECG signal. G. Petmezas et.al [**?**] extracted ECG features via a Convolutional Neural Network and then this features are fed to LSTM for time series based sequence analysis. This method gives higher efficiency for classification of four ECG classes. Deevi et,al [**?**] proposed highly efficient deep representation learning approach using denoising and beat classification module. They classify ECG beat into ten classes. A.Peimankar et.al [**?**] proposed DENS-ECG algorithm using CNN and LSTM netowrk for real-time segmentation of heartbeats.

3. Methodology

The ECG signal is normally made up of various frequency components and sometimes even noises, that increase the complexity of a deep-learning approach of extracting discriminatory features. Such variations and the small number of learning data available at each arrhythmia makes it challenging

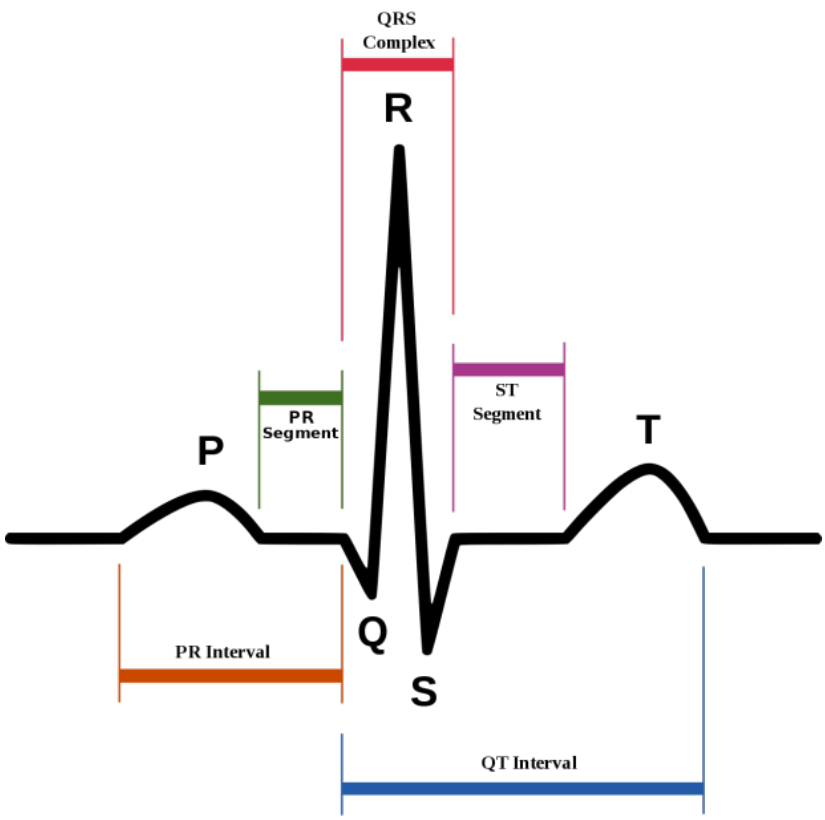

Figure 1: Typical ECG Waveform [?]

for conventional learning methods. In past few decades, there seems to be a considerable rise in advancement in ECG signal processing for application of automatic detection of different cardiac failure using machine learning technique.

Major problem arises due to various noise frequently occur in that ECG signals. Thos noises are, Power Line Interference, artifacts and Baseline Wander [? ? ?].This noise affect the classification results. Noise in the ECG is removed using Zero phase low pass filter. following results demonstrate the difference in the original and Filtered ECG signal. Red color indicates Filtered ECG and blue color ECG indicates Original raw ECG.

In this research a new extension of inception based layer is used to increase the efficiency of the traditional GAN for arrhythmia classification problem in ECG processing.

A. ECG Segment Separation:

Sequence of low-pass and High pass filter having transfer function is apply on ECG signal

$$H(z) = \frac{(1 - z^{-6})^2}{(1 - z^{-1})^2} \tag{1}$$

$$H(z) = \frac{(-1 + 32z^{-16} + z^{-32})}{(1 + z^{-1})} \tag{2}$$

Then the filtered signal Derivative followed by squaring function is taken,

$$H(z) = \frac{1}{8T}\left[-z^{-2} - 2z^{-1} + 2z^{1} + z^{2}\right] \tag{3}$$

$$y(nT) = [x(nT)]^2 \tag{4}$$

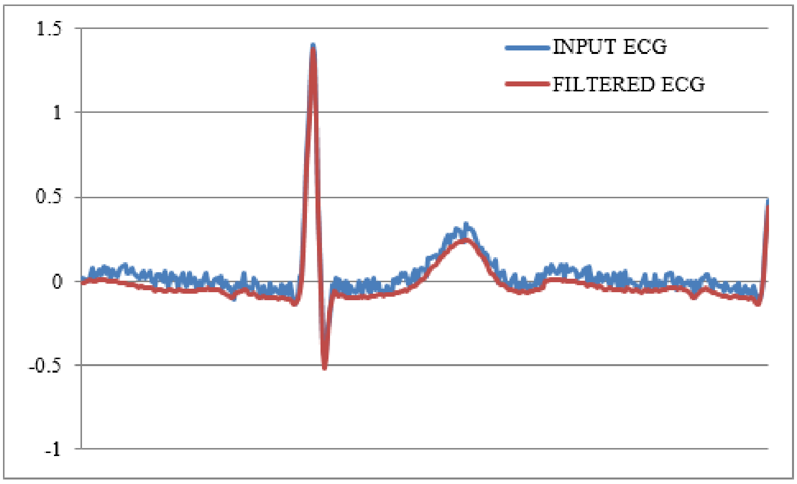

Figure 2: Original and Filtered Signal

(3) and (4) are the derivative and squaring function.After this peak detection is carried out. the threshold for peak detection is as follows,

$$D_t = NP_l + C_t(QRS_{pl} - NP_l) \tag{5}$$

B. General Generative Adversarial Network

The Conventional GAN architecture contains 2 modules, first is Generator and the second one is the Discriminator. Input to the generator is a random noise data which is processed and mapped this data to some 2D ECG type structures. Generator estimates its weight and bias randomly. Then this 2D data is fed to Discriminator for verification purpose. Discriminator then distinguish it to original ECG or generated ECG. Discriminator is also needs to train for the Original ECG and generated ECG. It then feedback the output to generator which again update its weight and bias. this again generated signal is fed to discriminator for classification.. Discriminator is trained for both real and fake data. It also update its weight and bias for classification purpose. Discriminator then successfully determine the real and false data [**?**].

ECG beat is one dimensional signal. To forward this beat to GAN architecture we need to make them 2D.For this purpose we convert 1D signal to 2D TF frame using daubechies wavelets transform. The scaling and wavelet function of the daubechies wavelets is as follows Scaling function and wavelet function is as follows:

$$\alpha_i = h_0 s_{2i} + h_1 s_{2i+1} + h_2 s_{2i+2} + h_3 s_{2i+3}$$
$$\alpha[i] = h_0 s[2i] + h_1 s[2i+1] + h_2 s[2i+2] + h_3 s[2i+3] \tag{6}$$
$$c_i = g_0 s_{2i} + g_1 s_{2i+1} + g_2 s_{2i+2} + g_3 s_{2i+3}$$
$$c[i] = g_0 s[2i] + g_1 s[2i+1] + g_2 s[2i+2] + g_3 s[2i+3] \tag{7}$$

The main aim of the proposed approach is to divide the existing ECG signals into different frequency ranges.

C. Proposed GAN

Proposed Inception based GAN (IDGAN) network for classifying the ECG beats is explained in following paragraph.

Let, $Ecgb(n) = [ecgb_1, \ldots, ecgb_n]]$ is 2D ECG signal and divided into ECG beats of each 1 sec, where, $eb1 = \{ecg1, \ldots, ecg10\}$ is the sample number of the ECG signal. It represent the 10 second signal where sampling frequency is 360 sample/sec. Each ECG is analysed in segment-wise. Main Contribution made to this methodology is we modify the traditional GAN architecture with improved loss function.

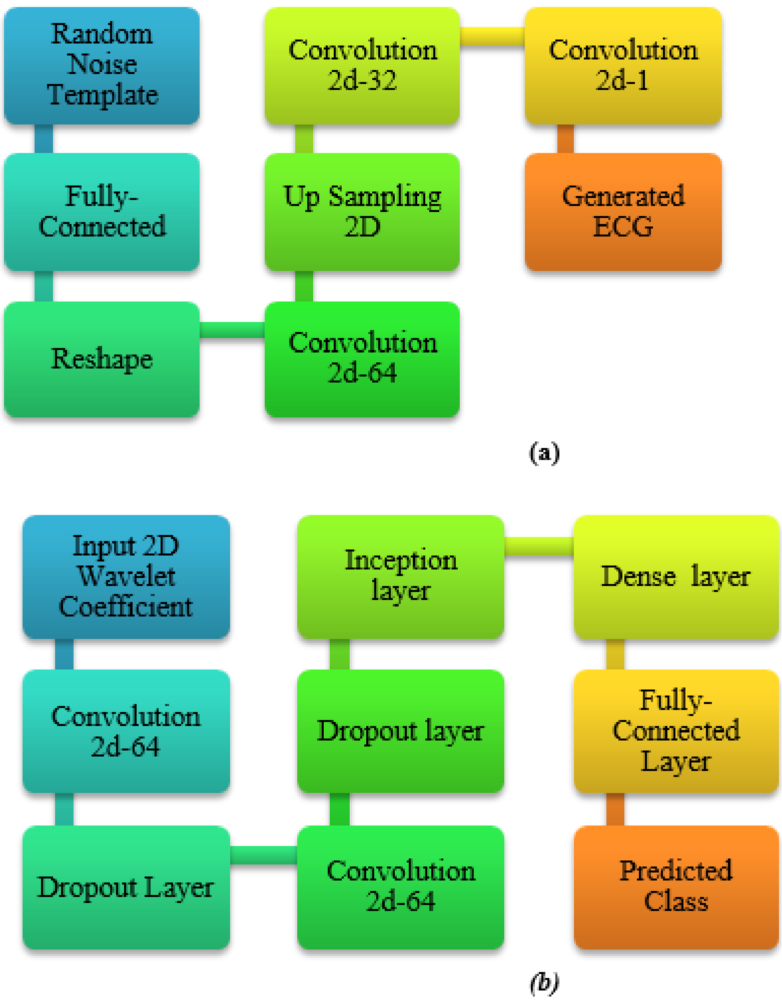

Figure 3: (a): Generator architecture, (b): Inception inserted discriminator architecture

This wavelet coefficient estimated form ECG beat is considered as a template for GAN based processing. The Generator $D(eb|z, \theta_D)$ predict the template form random Gaussian noise $p(eb|YW)$ The estimated template is W is having similar coefficient to original ECG template Y. This process take number of iterations. In each iteration error is calculated and if it is below than the threshold then this signal is estimated final template. The discriminator $D(G(c), eb_1, \theta_D)$ classify the first ECG Class eb and another $G(c)$ precisely. This Conventional GAN have only two classes i.e. it is in bianary form.To modify this to fit our application we added a well known concept of one against all. According to this strategy, every class is considered as an individual class against remaining class, irrespective of their old classes. i.e. while classifying S class all remaining classes for example N, V, F, and Q is considered as other class. $D(eb)$ is representation of the template eb. Basically G and D are the two player involved min-max game with value function $V(G, D)$. The optimal parameter of generator and discriminator by optimizing the value of function $V(G, D)$ is given as,

$$\min_{G} \max_{D} V(D, G) = E_{x \sim pdata(x)}[\log D(x)] + E_{z \sim pdata(z)}[\log(1 - D(G(z)))] \tag{8}$$

In layer wise architecture, The generator (G) consist of six layers whereas the discriminator (D) includes of seven layers. Three convolutionary layers together with single activation including its LeakyReLU and at the end one activation of a tanh create the generator.

Similarly, two convolutionary layers with LeakyReLU activations as well as one fully-connected SoftMax layer just at end make the discriminator. Dense layer is attached as well. The dropout rate for Dropout layers is kept to 0.3. It will help to decrease the impact of over-fitting.

DWT based 2D tensor termed as template is used as a input of the first layer i.e. to Conv layer:

$$X = [x_1, x_2, \ldots, x_k]$$

in this k denotes of the template sample at each index. To increase the system performance interms of execution and efficiency, the Max-Min Normalization is carried out to $[0, 1]$ range.

$$x = \frac{x - min}{max - min} \tag{9}$$

Min-max term in above equation indicates the minimum whereas max indicates the maximum value at each channel. After this operation reshaping of data for further processing is implemented. This reshaped data is further passed to Conv layer.

The output of the jth feature map on the ith unit of the l convolution layer is:

$$x_i^{l,j} = \sigma[b_j + \sum_{a=1}^{m} w_a^j x_{i+a-1}^{l-1,j}] \tag{10}$$

Where, bias term for jth feature is indicated with bj, size of kernel is indicate by m. Weight is w_a^j of j th feature coefficient and of filter index(ath). Activation function is indicated by σ.

Table 1: Proposed GAN layer

Layer	Generator	Discriminator
0	Random Noise Template	Input 2D Wavelet Coefficient Template
1	Fully- Connected	Convolution 2d-64
2	Reshape	Dropout Layer
3	Convolution	2d-64 Convolution 2d-64
4	Up Sampling 2D	Dropout layer
5	Convolution 2d-32	Inception layer
6	Convolution 2d-1	Dense layer
7	-	Fully- Connected Layer

D. Training Criteria

To reach the training criteria sum of two cross-entropy function H is used,

$$\begin{aligned} Loss(D) &= H(real_{eb}, 1) + H(eb_1, 0) \\ &= [-1 \times \log D(real_{eb}) - (1-1)\log(1 - D(eb_{real}))] \\ &+ [-0 \times \log D(eb_g) - (1-0)\log(1 - D(eb_g)] \\ &= -\log D(eb_{real}) - \log(1 - D(eb_g)) \end{aligned} \tag{11}$$

where, $eb_g \sim pdata(eb)$ is eb_{real} is an template of individual class and eb_g is template of remaining class irrespective of the original class.

Another criteria is the execution time required for the system among all convolution layers.

$$O(\sum_{l=1}^{d} n_{l-1}.s_1^2.n_1.m_1^2) \tag{12}$$

Here convolutional layer index is indicated as 1, and convolutional layers number is indicated by d. Total used filters numbers is n at layer l layer. Spatial size of the filter is s whereas spatial size of output feature map is m. Its time cost with fully - connected layer as well as pooling layers is always 5-10 percent computational time, that were not included in abovementioned composition.

4. Experiment & results

The MIT-BIH Arrhythmia Dataset is described below. Total patients involved is 47.This collected ECG samples are classified into five clinical super classes and Fifteen subclasses by AAMI [**?**];

To test the system reliability local database from private hospital is also collected. This data contains large noise. This recordings were collected from 34 patients out of this 11 are females having age in between 39 to 61 and 23 males having age in between 34 to 53. This ECG recording are also grouped into 15 classes of cardiac dysfunctions with the assist of cardiac specialist. This signals were sampled at a sampling frequency of 360 Hz and having duration of 1 minute. This signal are then converted to 10 sec segments.

Total we have collected 1060 samples. out of this 700 segments are used for training purpose. Remaining 360 are used for validation and Testing purpose.

Implemented IDGAN is validated on the fusion of two dataset i.e on MIT-BIH and real time hospital data [**?**]. This two dataset have long recording duration, so for simplicity we convert then in 10 seconds segment. Then this segments are then further divided into training and testing part. 360 samples are used for testing. This testing samples are from Fifteen class and one unknown class which we labelled as unclassifiable.

Performance Criteria:

To test proposed system reliability, we used following criteria for proposed and well known state art of the method. Well known state art of the method is implemented and tested on same dataset with same training and testing strategy.

True Positive [TP]: Accurately classified as a current class
True Negative [TN]: Accurately classified as a remaining class
False Positive [FP]: Falsely classified as a current class
False Negative [FN]: Falsely classified as a remaining class

Table 2: Class label information of the arrhythmia database

No	Heartbeat Type		ECG Signal
1	Normal Rhythm	NOR	41
2	Left Bundle Branch Block	LBBB	24
3	Right Bundle Branch Block	RBBB	22
4	Atrial premature Contraction	APC	21
5	Premature Ventricular contraction	PVC	31
6	Paced Beat	PB	12
7	Aberrated Atrial Premature Beat	AP	18
8	Ventricular Flutter Wave	VF	15
9	Fusion of Ventricular and Normal Beat	VFN	23
10	Non Conducted P-Wave (Blocked APC)	BAP	18
11	Nodal (Junctional) Escape Beat	NE	16
12	Fusion of Paced and Normal Beat	FPN	13
13	Ventricular Escape Beat	VE	19
14	Nodal (Junctional) Escape Beat	NP	21
15	Atrial Escape Beat	AE	27
16	Unclassified Beat	UN	39

Accuracy=[TP + TN] / [P + N]
Specificity=[TN] / [N]
Sensitivity=[TP]/[P]
False Negative Rate=[FP]/[P]

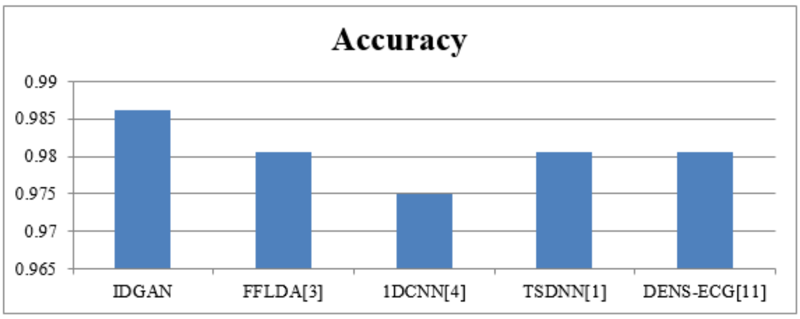

Figure 4: Comparison of accuracy

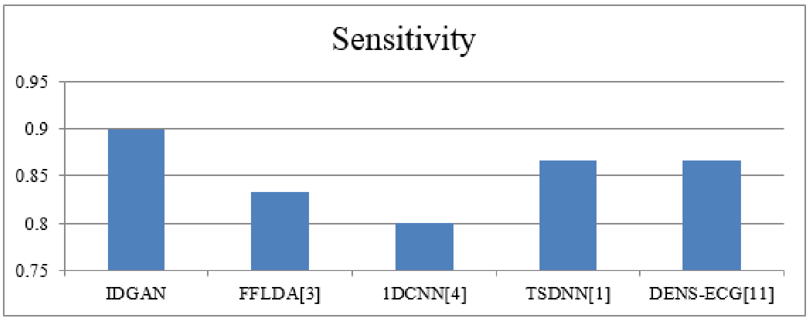

Figure 5: Comparison of sensitivity

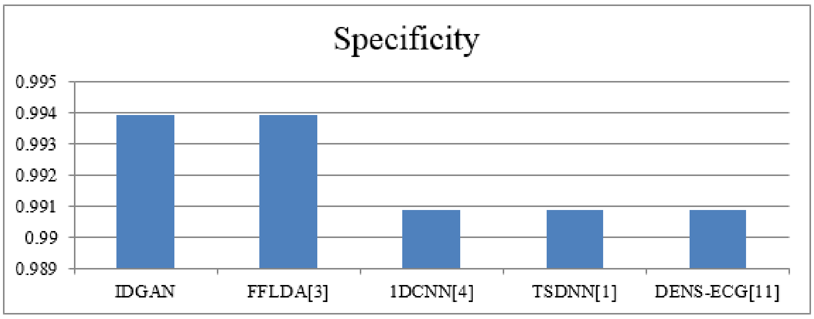

Figure 6: Comparison of Specificity

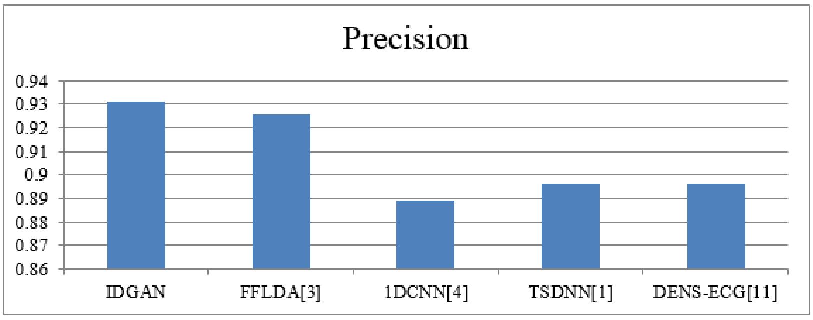

Figure 7: Comparison classes of precision

5. Conclusion

Cardiovascular disease must be correctly diagnosed and appropriate treatment for the same must be given promptly to patients in order to decrease the death rate. To the best of our knowledge, Current implemented technique is the only one that integrate inception layer to Generative Adversarial Network right after the wavelet decomposition for ECG signal processing. Due to integration of inception layer proposed method can look deeper into the ECG template. The implemented IDGAN technique was tested on the PhysioNet MIT-BIH Database and some hospital data for the ECG classification of 15 major types of heartbeats. It can be inferred from the results that the proposed approach is smart enough to make meaningful predictions and produces excellent performance on the related metrics. Our experiments with these techniques achieved overall accuracy of 98.6%, precision above 93.1%, specificity above 99.39%, and sensitivity above 90.0%.

6. Discussion

This paper proposes an effective and convenient approach to ECG interpretation using novel technique, that will probably used in regular practice. The proposed model is applied to the MIT-BTH dataset and one hospital data which is more imbalanced dataset with shorter data of 10 sec. Our experiments with these techniques achieved overall accuracy of 98.6%, precision above 93.1%, specificity above 99.39%, and sensitivity above 90.0%.

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