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Arrhythmia Classification Using Noise Filtering and 1D CNN

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ABSTRACT

Identifying arrhythmias in electrocardiogram (ECG) data is critical for diagnosing and managing heart disorders. However, various types of noise in ECG data frequently pose a challenge to proper arrhythmia classification. To overcome this challenge, this study suggests a three-step process to make it more accurate to classify arrhythmias as normal (N), supraventricular (S), ventricular (V), fusion (F), or unknown (Q). In the first step of the three-step process, we add Gaussian noise to the MIT-BIH ECG data to make the classification model more reliable. Second, ECG signals are notch-filtered to eliminate noise artifacts and preserve cardiac information after Gaussian noise injection. Retaining important cardiac information while reducing noise distortion. Third, the 1D CNN receives denoised ECG data for arrhythmia classification. Five-class arrhythmias can be used to examine the ECG signals, according to the results of the suggested modeling. With a 1% error rate, the 1D-CNN-based classification system can identify N, S, V, F, and Q with 99%, 86%, 96%, 80%, and 99% accuracy. The results suggest that the three-step ECG arrhythmia categorization method improves diagnostic accuracy, enabling early treatment by healthcare experts. Its real-world applications improve cardiovascular diagnosis and patient outcomes.

1. INTRODUCTION

Cardiovascular disease (CVD) is the world's leading cause of death, killing 17.9 million people annually. Modern methods for finding and analyzing heart problems are needed right away to make sure that people with these heart problems can get the right medical care at the right time [1]. The proliferation of ubiquitous electronics and data transmission infrastructure advancements in recent years has facilitated the accessibility of devices integrated with wire- less sensors [2]. This has essentially enabled the continuous monitoring of human health. Arrhythmias affecting the heart are of significant importance due to the critical function the heart assumes in blood circulation and its contribution to the progression of CVDs.

Arrhythmia, which is defined by irregular heartbeats, dis turbs the cardiac rhythm by producing symptoms that are excessively rapid, decelerating, or occurring in an erratic pattern. The severity of this disruption in the heart's regular rhythm can range from minor to potentially critical [3]. Employing the ECG as a diagnostic instrument is of immense value when it comes to recording and analyzing the electrical activity of the heart. Arrhythmia is frequently detected and managed with this non-invasive procedure in routine cardiac monitoring [4]. The ECG has become a conventional medical instrument for accurately monitoring heart rates [5] by capturing the electrical impulses of the heart during blood circulation. Decoding ECG data, on the other hand, requires specialized expertise and manual interpretation is laborious, time-consuming, and susceptible to human error. It is believed that an automated computational approach is crucial in order to tackle these challenges.

Based on the patterns found in ECG recordings, cardiac arrhythmias are classified in various ways. most instances include morphological and rhythmic arrhythmias. Rhythmic arrhythmia is represented by a sequence of irregular heart-beats that follow a regular pattern, whereas morphological arrhythmia is marked by a single abnormal heartbeat. Arrhythmias may also be classified according to the chamber of the heart that is affected, resulting in subtypes including tachycardia or supraventricular arrhythmia (SVA), premature or additional pulse, bradyarrhythmia (BA), and ventricular arrhythmia (VA) [6].

There are two main groups of researchers who can classify cardiac rhythm abnormalities. The first uses conventional machine learning, which entails three stages: (1) preprocessing the ECG signal, (2) feature extraction and selection, and (3) ECG classification. The second uses deep learning techniques to train classifiers from scratch using only the data they were given to work with. Because of this, we may forego the subjective and limiting custom features [7].

The surface electrical potentials of the heart are recorded during an electrocardiogram (ECG), reflecting the organ's stimulation rather than its contraction. A One-lead ECG wave for a typical cardiac cycle [8] is shown in Figure 1.

Horaceket al. [9] and Malmivuo and Plonsey [10] provided a more in-depth analysis of the physiological principles behind cardiac electrophysiology. Kligfield et al. [11] describes the one-lead waves of a normal heart cycle:

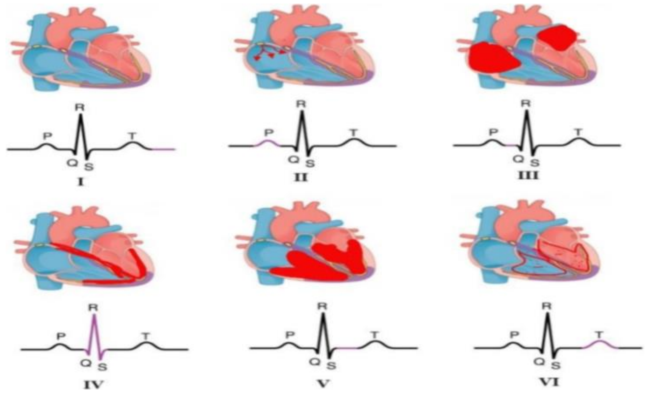

Figure 1. A typical cardiac cycle in one-lead ECG [8]

I. Atrial Systole: The heart's lowest point of length occurs during this relaxation phase, called atrial diastole.

II. P wave: During weak atrial systole, the P wave is brief (with an amplitude of 0.4 mV or less), and its duration is between 60 and 120ms, indicating atrial activity. The accurate identification of atrial flutter in the heart can be aided by measuring this interval.

III. PQ stretch: An unbroken stretch of time between the heart's atrial and ventricular beats. Between 12 and 20 milliseconds is the average PQ interval.

IV. QRS complex: The three pulses (Q, R, and S) of the left ventricle reflect the depolarization of different regions. Varying times of the QRS complex have been associated with the occurrence of arrhythmia, fibrillation, and myocardial infarction. The typical range is between 60 and 90 milliseconds.

V. ST stretch: This segment extension occurs approximately at the baseline of the electrocardiogram signal, following the S wave and preceding the T wave. It occurs between 230 and 460 milliseconds and is characterized by the contraction and subsequent relaxation of the ventricles. By analyzing ST duration, ischemia complications can be identified more precisely.

VI. T wave: The T wave represents the ventricles' activation period, during which they become prepared to contract again. The T wave's prolonged duration (100 to 250 milliseconds) makes it easier to detect cardiac hypertrophy, heart failure, and ischemic heart disease.

1.1 Key challenges in existing ECG arrhythmia classification systems

Aljuaid et al. [12] highlighted that monitoring devices' manual static screening in homes is limited. ECG Check, Kardia, and cardiac monitoring smartphone apps may be challenging for elderly or illiterate patients to use. To improve frequent monitoring compliance, home manual monitoring systems should include alerts and reminders.

Real-time monitoring installations suffer signal quality challenges [13]. To eliminate motion artifacts during physical activity, they stressed the importance of filtering. Their noise reduction method uses an accelerometer.

Bianchi et al. [14] addressed real-time remote monitoring of ECG signal data size challenges. They noted the necessity of clever feature extraction techniques to choose informative signal time periods. This step is essential before sending condensed data to a distant station for interpretation.

Gusev et al. [15] described continuous ECG monitoring and visualization challenges. Managing refreshing rate needs across many platforms on lower-processing devices was the main difficulty.

Baig et al. [16] discovered clinical decision support model system integration challenges. They focused on scalability and dependability, suggesting further study. The authors suggested real-time processing on the cloud to solve integration issues.

In addition to the challenges, ECG monitoring systems face complicated computing demands, energy harvesting, and patient opposition to using monitoring devices. The use of mobile devices in continuous ECG monitoring raises concerns such as limited computing capability for data-intensive processing and battery depletion. While mobile devices improve monitoring flexibility, overcoming these limitations is a continuing problem.

In conclusion, this work introduces a cutting-edge deep-learning model for arrhythmia classification from ECG data. We want to improve the model's performance by methodically preprocessing the signals, which will include advanced filtering techniques and dataset augmentation. We will further explore our novel technique in the following sections, emphasizing the use of a flexible deep convolutional neural network architecture for feature extraction. Finally, our study will clarify the aims and offer a clear summary of the next parts, demonstrating the model's usefulness in tackling issues connected with ECG arrhythmia categorization.

The rest of this paper will be structured as follows: Section 1 covers the fundamentals of cardiovascular disease, arrhythmia, and the categorization of arrhythmias. In Section 2, we give a comprehensive literature review centered on earlier research into ECG-based arrhythmia detection. Section 3 provides background for the suggested method. In Section 4, we detail the method we recommend in detail. Section 5 contains the presentation and interpretation of the researchers' experimental findings. In Section 6, we can provide a conclusion and talk about how people might improve objects in the future.

2. RELATED WORK

Here, we have a look at the various initiatives taken by researchers to enhance ECG arrhythmia classification. Due to background noise, ECG readings might be difficult to interpret correctly. Furthermore, a high level of competence is necessary to understand the ECG findings. Therefore, several accurate and automated approaches for ECG signal processing have been proposed by researchers over the years [17]. Most of the work done in the past to better interpret arrhythmias from ECGs has focused on signal processing. In this follow, this article will take a closer look at the studies that have been undertaken in this section.

2.1 Categorizing approaches by signal processing

Sodmann et al. [18] have investigated various approaches to arrhythmia identification, exhibiting a variety of deep learning and signal processing methods. An anonymous writer used a neural network design with Fourier and dynamic wavelet transforms, and the result was an excellent 82% F-score. Zairi et al. [19] achieved an impressive classification accuracy of 98.3% by combining the use of a discrete wavelet transform (DWT) with a multilayer perceptron (MLP). A deep deterministic learning (DDL) approach using synthetic neural network frameworks was presented by Iqbal et al. [20], who achieved an exceptional 98% total accuracy. Using deep learning on highly linked one-dimensional neural networks, Cai et al. [21] produced an amazing 99.35% classification accuracy with a focus on atrial fibrillation (AF). In their investigation of rhythmic fluctuations, Maglaversa et al. [22] used a radial-based function network (RBFN) for efficient classification and improved QRS complex detection.

With an SVM architecture and growing neural networks, Pławiak [23] presented a method that achieved outstanding accuracy of 98.85% and specificity of 99.39%. By using preprocessing methods and a modified deep learning architecture, Kanani and Padole [24] effectively implemented deep learning tactics, improving the classification accuracy of cardiac arrhythmias. Çınar and Tuncer [25] used LSTM with hybrid CNN-SVM deep neural networks, contributing to continuous monitoring of cardiac abnormalities. Sharma and Dinkar [26] presented the LA-SCA approach, using a deep neural network with discrete wavelet preprocessing for accurate arrhythmia classification. Sharma et al. [27] classified arrhythmias using a feedforward back-propagation neural network and the cuckoo search approach.

An actor-critic (AC) neural network trained in the Taylor-Sine-Cosine algorithm was utilised by Vylala et al. [28]. With an astounding accuracy rate of 97.7%, Yang and Wei [29] proposed a classification technique for electrocardiograms (ECGs) utilising SVM, KNN, and ANN. Asgharzadeh-Bonab et al. [30] extracted features using a convolutional neural network (CNN) and spectral entropy, obtaining 98.33% total reliability. A wavelet decomposition-based approach for feature extraction and classification utilising the hidden Markov model (HMM) was presented by Sangaiah et al. [31]. This method achieved a 99% success rate, despite a short sample size problem.

Huang et al. [32] demonstrated the effectiveness of a short-time Fourier transform for ECG data, which was followed by 2D-CNN classification. Oh et al. [33] successfully divided the ECG signal into sub-bands using a convolutional neural network (CNN) and a long short-term memory network (LSTM). Wavelet-based decomposition for ECG data was investigated by Yildirim et al. [34], who used unidirectional (ULSTM) and bidirectional (Bi-LSTM) neural network architectures for classification. Li et al. [35] demonstrated the possibility for classification improvement by training a generalised CNN neural network (GCNN) with multiple heartbeats and a specialised CNN (TD-CNN) approach. Together, these studies highlight the wide range of deep learning and signal processing methods that are advancing the field of arrhythmia identification.

In Table 1, a comprehensive summary of studies on ECG arrhythmia classification using signal processing approaches is provided.

2.2 Limitations in existing studies

Many studies have limitations that should be considered despite advances in arrhythmia detection. Sodmann et al. [18-21] found that complicated neural network designs are difficult to understand. These models' interpretability limits their use in clinical situations where decision-making is critical.

Studies like Iqbal et al. [20] and Sharma et al. [27] use publicly available datasets or personal samples, which presents data availability and quality issues. The use of finite datasets raises generalizability difficulties, and data quality may affect model predictions. According to Yang and Wei [29] and Sangaiah et al. [31], small sample numbers complicate the issue and may reduce the robustness of proposed techniques.

Preprocessing sensitivity is another drawback of LA-SCA [25]. These methods use discrete wavelet preprocessing, which raises questions about their applicability across datasets and cardiac circumstances. Vylala et al. [28] found that sophisticated approaches' computational complexity may hinder their adoption in resource-constrained contexts.

Maglaversa et al. [22] and Çınar and Tuncer [25], which study specific arrhythmias, worry about generalisation. Models may not be applicable to a wider range of cardiac disorders, and Sharma et al. [27] demonstrate the difficulty of optimising neural network weight variables.

Method efficacy concerns, especially in small sample sizes like Sangaiah et al. [31], cast doubt on generalizability to bigger and more diversified datasets. CNNs lack inherent explainability, which is critical in medical contexts, making their interpretation in Huang et al. [32] difficult.

Finally, Li et al. [35] balance model complexity and interpretability by using a generalised CNN neural network (GCNN) with a specialised CNN. Achieving a harmonious equilibrium in arrhythmia categorization remains difficult. These limitations demonstrate the complexity of arrhythmia detection studies and the necessity for continued research to overcome them and develop the field.

In conclusion, our three-step ECG arrhythmia categorization method is distinctive. The technology uses cutting-edge signal processing to improve cardiovascular diagnosis accuracy and overcome major research difficulties. The novel methods increase classification accuracy and cardiovascular diagnostic knowledge. According to the literature, the proposed method has evolved extensively, demonstrating its ability to overcome restrictions and progress in ECG arrhythmia categorization.

Table 1. Arrhythmia classification studies: signal processing approach

Reference	Signal Processing Method	ML/DL Model
[18]	FTWT	CNN
[19]	DWT	MLP
[20]	SNN	DDL
[21]	1D-NN	1D-NN
[22]	RBFN	RBFN
[23]	NN, SVM	NN, SVM
[24]	DL	DL
[25]	DWT	FFBPNN
[26]	CNN-SVM	CNN-SVM
[27]	FFBPNN	FFBPNN
[28]	AC-NN	AC-NN
[29]	SVM, KNN, ANN	SVM, KNN, ANN
[30]	CNN, 2D-PCA	CNN, 2D-PCA
[31]	HMM	HMM
[32]	STFT	2D-CNN
[33]	LSTM	ULSTM
[34]	WLSTM	ULSTM
[35]	GCNN	GCNN, TDNN

3. BACKGROUND

It is essential that we understand the reasoning behind the choice of Gaussian noise and Notch filtering as essential preprocessing steps before looking into the details of our approach. We specifically selected these methods to improve the realism and quality of the ECG signals being studied in different areas.

3.1 Optimizing ECG signal quality: Gaussian noise simulation and targeted notch filtering

Real-world recordings of ECG signals are subject to noise from a variety of sources, including physiological and environmental factors [36]. We introduced Gaussian noise to the ECG data to strengthen our model's robustness and simulate the challenges encountered in real-world applications. We include Gaussian noise in the ECG data to provide a more realistic representation of the noise patterns found in real-world recording scenarios. To ensure that the model can generalize effectively, we train and assess it using data augmented with Gaussian noise in less-than-ideal conditions. After that, we employed notch filtering to eliminate interference at certain frequencies while maintaining signal integrity overall. We chose notch filtering because it precisely targets and minimizes noise at specific frequencies, saving essential sections of the ECG signal. Our technique ensures that the ECG data used in the classification model is of higher quality by rapidly removing unwanted artifacts.

3.1.1 Benefits of gaussian noise addition

We intentionally added Gaussian noise to the ECG data, as it serves two benefits. This addition accomplishes two goals. First of all, it simulates the inherent noise present in real-world ECG recording settings [37], guaranteeing that our model is capable of managing difficulties faced in practice. Second, by exposing our model to different noise levels, the addition of Gaussian noise improves its generalization skills and lets us evaluate how resilient our model is.

3.1.2 Advantages of notch filtering for targeted noise reduction

Times Notch filtering reduces certain sources of disturbance in the ECG signals. Notch filtering preserves important signal characteristics by focusing on and removing undesirable frequencies [38]. The integrity of the ECG data depends on this accuracy in noise reduction because general filtering techniques may unintentionally smooth out important information. As a result, the fundamental cardiac activity is more accurately and cleanly represented, providing a strong basis for further investigation.

3.2 MIT-BIH database

The cardiac impulses utilized in this research were taken from the arrhythmia database at the MIT-BIH [39]. There is a wide variety of heartbeats represented in the database, which was built from 48 recordings submitted by 47 different people. which was built from 48 recordings submitted by 47 different people. Bandpass filtering between 1 and 100 Hz and 360 Hz sampling gives each file a duration of 30 minutes. The dataset includes a modified limb II channel and a modified lead channel (V1, V2, V4, or V5). In this investigation, studies used a specialized form of the limb II channel [40]. Each heartbeat was analyzed by a different team of specialists, who labeled it with an arrhythmia classification. Normal ectopic (N), ventricular ectopic (V), fusion (F), supraventricular ectopic (S), and unclassifiable (Q) are the five types of abnormal heart rhythms defined by the Association for the Advancement of Medical Instrumentation (AAMI) [41]. Thus, five different arrhythmias were detected by segmenting according to the AAMI recommendations. For each category of arrhythmia, the total number of heartbeats is detailed in Table 2. Each ECG performed further processing to identify the individual heartbeat [42].

Table 2. Number of ECG beats based on AAMI

Arrhythmia Type AAMI	**MIT-BIH Heartbeat Classes**	**Beat Count**
Normal (N)	Beats of normal, right, left bundle block, atrial, nodal escape	8965
Supraventricular (S)	Ectopic supraventricular, nodal, atrial aberrated atrial premature beats contraction	2779
Ventricular (V)	Ventricular contraction, flutter, beats of premature	7236
Fusion (F)	Fusion of ventricular and beat of normal	803
Unknown (Q)	Unclassifiable fusion of paced and normal, beats of paced	8006

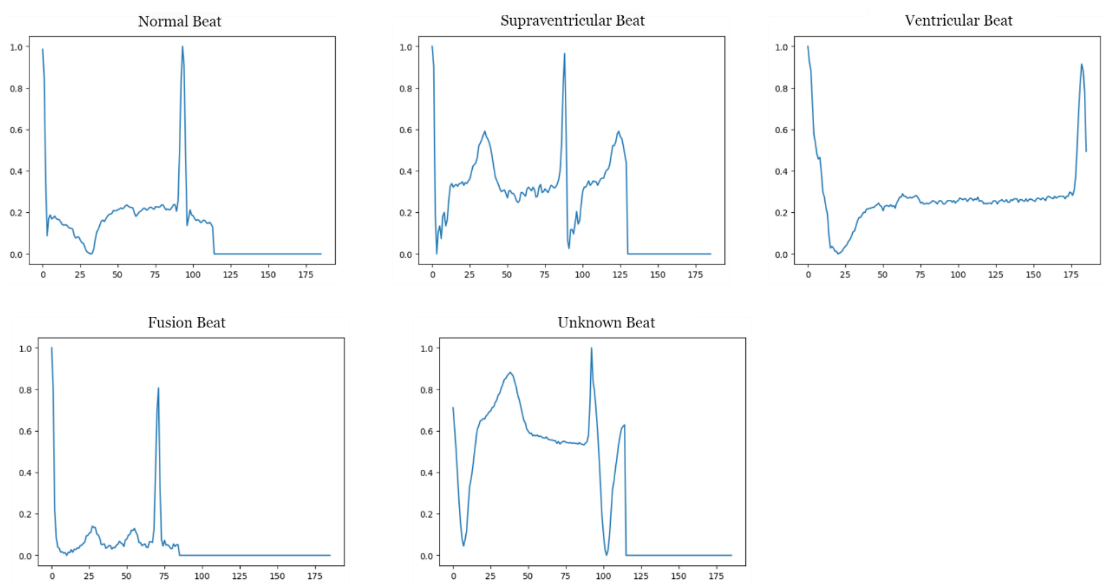

Figure 2. Original ECG into segmented ECG signals

The Python Workbench was utilized to segment heartbeats by identifying the QRS structure of the signal's pulses in order to extract annotated beats. A demonstration of an annotated rhythm is presented in Figure 2.

3.3 Simulating ECG signals with Gaussian noise

Adding Gaussian noise to images during training is a smart strategy to enhance the robustness of image classification models. This approach compels the model to develop features that can withstand minor variations in the input. This becomes particularly beneficial when dealing with training data that is either lacking or highly diverse [43]. It's like giving the model a set of challenges during training, preparing it for real-world scenarios where input conditions may not always be perfect. The ECG signal $x(t)$ is amplified through the introduction of Gaussian noise $N(t)$. This could be formulated as:

$$P(x) = 1/(sqrt(2\pi\sigma^2))*e\hat{}(-((x\text{-}v)^2) / (2\sigma^2))$$

In this case, "Sigma" represents the standard deviation of our improvements, and "Mu" denotes the zero-mean value. By supplementing the ECG with the noise signal, it is possible to obtain the augmented ECG signal, represented as $x(t)+N(t)$.

Algorithm: Simulating ECG Signal with Gaussian Noise (Conditional)

1. Set sampling frequency (fs) = 1000
2. Set sampling period (Ts) = 1/fs
3. Generate time vector: t = 1: Ts:10-Ts
4. Set signal frequency (f) = 1 (Frequency in Hz)
5. Set signal amplitude (a) = 1
6. Generate sinusoidal signal: signal = a * sin (2π * f * t)

If adding Gaussian noise:

7. Set noise frequency (f Noise) = 50 (Frequency in Hz)
8. Set noise amplitude (a Noise) = 0.25
9. Generate noise: noise = a Noise * sin(2π *f noise * t)
10. Combine signal and noise: signal Noise = signal + noise

Else:

11. Use original signal: signal Noise = signal

Probability Density Function (PDF) of Gaussian Distribution:

If computing PDF:

12. Set mean (μ) = mean of signal Noise
13. Set standard deviation (σ) = standard deviation of signal Noise
14. Compute $P(x) = 1/(\sqrt{(2\pi)}\sigma) *e\hat{}(-((x-\mu)^2) / (2\sigma^2))$

The algorithm utilized to simulate an electrocardiogram (ECG) signal provides the capability to employ Gaussian noise selectively. As critical sampling parameters, a sampling frequency (fs = 1000 Hz) and period (Ts = 1/fs) are specified. An ECG sinusoidal signal with frequency (f = 1 Hz) and amplitude (a = 1) is generated over a duration of 10 seconds. A noisy ECG signal (signal noise) is produced when the noise condition is triggered and frequency (f noise=50 Hz) and amplitude (a noise=0.25) Gaussian noise are added to the original signal. The initial signal remains unaltered when the noise condition is absent. For noisy ECG data, the algorithm also provides the option to compute the probability density function (PDF) of a Gaussian distribution. The mean and standard deviation are derived from the signal statistics, and the $P(x)$ value is computed utilizing the formula for the Gaussian distribution. For the modeling of ECG signals, this algorithm offers a straightforward and adaptable solution, which consists of dynamic noise management and, if desired, statistical analysis. As a visual representation, the resulting chaotic ECG signal (signal noise) is then illustrated in the Figure 3.

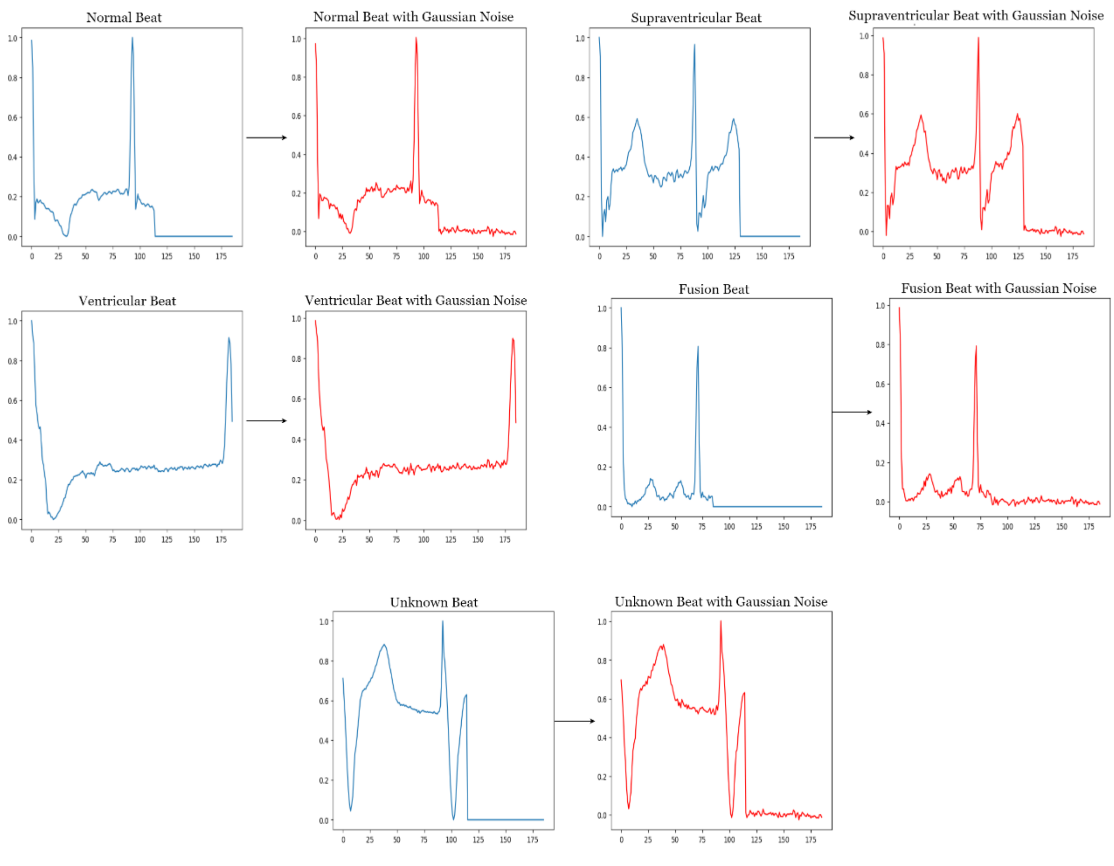

Figure 3. ECG signals with gaussian noise

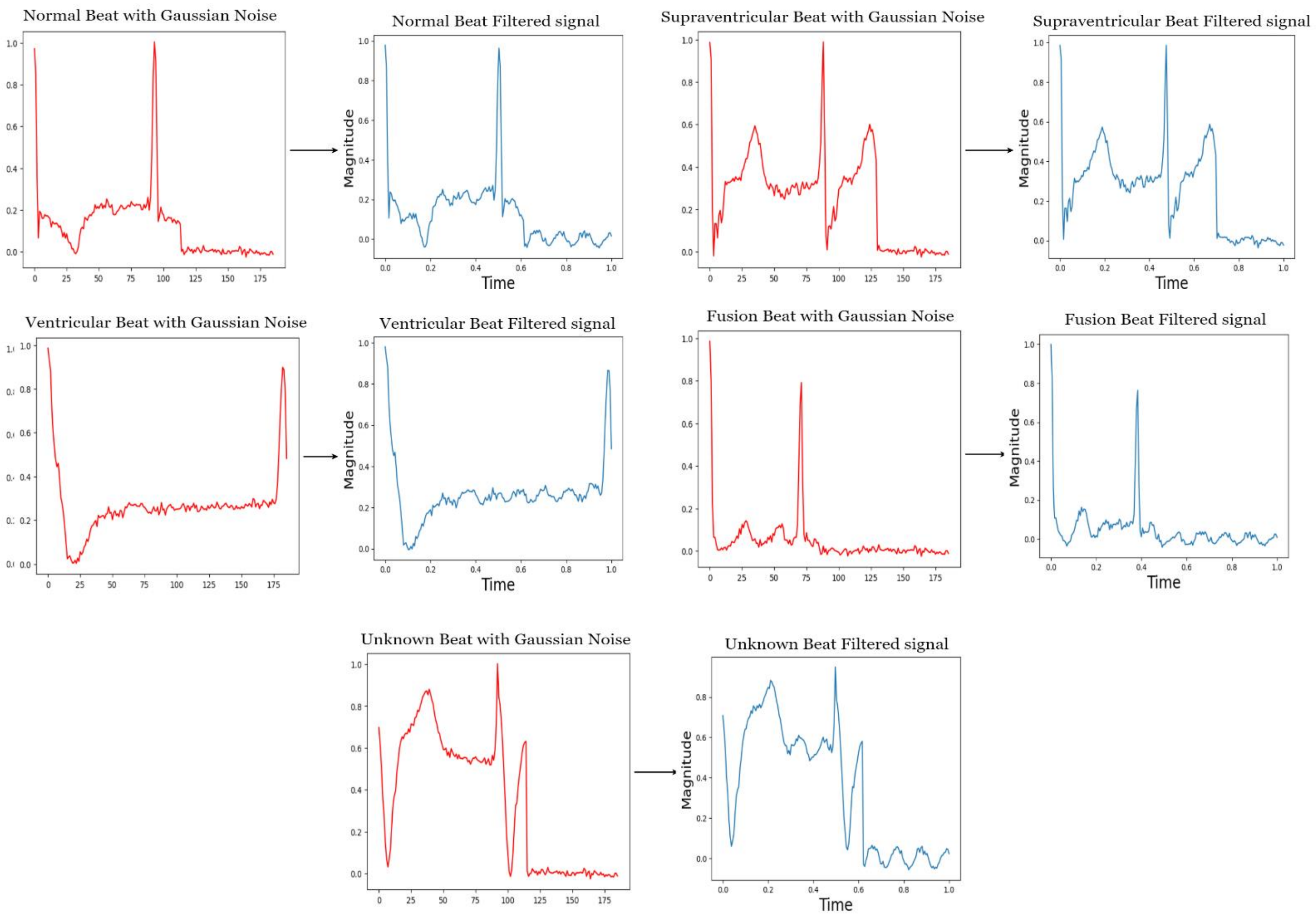

Figure 4. Output of the notch filter with ECG signals

3.4 Notch filter for noise elimination

When compared to band-stop filters, notch filters perform identically. These filters reduce or block signals just in the stop band, allowing those outside it to pass through un- changed. A notch filter with a stop band frequency of 1500 MHz to 1550 MHz will block signals over 1550 MHz while letting frequencies between DC and 1500 MHz through. Only those transmissions between 1500 and 1550 MHz will be blocked [44]. A dedicated Notch filter is quickly integrated into the signal processing pipeline to further enhance the algorithm's capabilities. This unique filter is specifically developed to remove Gaussian noise from high-resolution ECG signals, with an emphasis on frequencies between 50 and 60 Hz. The Notch Filter, which is handcrafted, assures a spike-free ECG signal with minimal interruption to the original signal's frequency distribution.

The Notch Filter's efficiency comes from its quick calculation process and simple programming, which takes advantage of an integer coefficient filter technique. The ECG signals undergo a modification that makes them particularly beneficial for categorization after being filtered with Gaussian noise using the Notch Filter. Figure 4 depicts this procedure, demonstrating the Notch Filter's effectiveness in maintaining critical diagnostic information while quickly reducing undesirable noise components. The obtained ECG signals provide a solid foundation for further analysis and categorization.

The Notch Filter algorithm is designed to eliminate Gaussian noise from ECG signals. It employs a second-order IIR filter with a user-defined center frequency (f center) and bandwidth (BW). Coefficients a, b, and c are computed for the filter. The filtering process is executed on the noisy ECG signal (signal noise), resulting in a spike-free and enhanced ECG signal (filtered Signal). Adjustments can be made to the parameters for specific noise removal requirements.

Algorithm: Notch Filter for ECG Signals

1. Set Sampling Frequency:

- Sampling Frequency (fs): [50-60 Hz]

2. Design Notch Filter:

- Power Line Frequency (f Powerline): [60 Hz]
- Calculate Angular Frequency (w Notch):

2π * f Powerline / fs

- Design Notch Filter Coefficients:
- *b* = [1, -2 * cos (w Notch), 1]
- *a* = [1, -2 * cos (w Notch), 1]

3. Apply Notch Filter to ECG Signal:

- Input ECG Signal: ECG Signal
- Output Filtered Signal: ECG Filtered = filter (*b*, *a*, ECG Signal)

4. Visualization:

- Plot Original ECG Signal and Filtered Signal for comparison

4. METHODOLOGY

This section presents the classification of the Arrhythmias using One-Dimensional CNN (1DCNN). Figure 5 shows the pipeline of the classification process of Arrhythmias using

1DCNN with the help of extracted, handcrafted features. This section provides an overview of the categorization of Arrhythmias using One-Dimensional Convolutional Neural Networks (1DCNN).

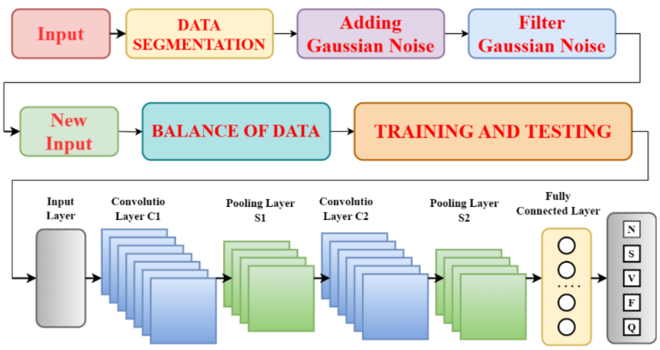

Figure 5. Classification of arrhythmias using 1DCNN

4.1 Rationale for choosing 1DCNN in ECG classification

One of the reasons a 1D Convolutional Neural Network (1D CNN) was used for ECG classification is that it can effectively capture localised temporal patterns that are important for identifying cardiac problems. ECG signals are known to display subtle fluctuations, and the translation invariance of the 1D CNN helps identify these patterns even when there are temporal shifts. Furthermore, the network is well-suited for the complex and changeable nature of ECG data because of its hierarchical feature learning, computational efficiency, and flexibility for variable-length sequences. Less reliance on parameters means faster training and less chance of overfitting, while convolutional filters' interpretability makes it easier to comprehend how the model makes decisions. All things considered, the 1D CNN's proficiency with time-series data and its ability to extract both local and global characteristics make it an attractive option for ECG classification applications.

4.2 Training procedures for ECG classification

The architectural design used 1D CNNs for ECG categorization. The input (187, 1) underwent ReLU activation after applying three one-dimensional convolutional (1DCav) layers with filter dimensions of 32, 64, and 128. The network's feature capture and generalisation were improved by adding max-pooling, dropout, and flattening layers. The last classification stages used dense layers-a thick layer with three levels of 512, 1024, and 5 units. The output layer provided five classification reports reflecting the multi-class job, with a structure of (5, 1).

Multi-class classification was optimised using categorical cross-entropy as the loss function during training. To maximise convergence and performance, the Adam optimizer was used to adjust the learning rate. Strategic dropout in deep layers reduced overfitting and improved generalisation to unseen data. Monitoring validation performance prevented overtraining and improved model generalisation to fresh ECG signals by using early stopping.

These training approaches make the 1D CNN model robust and successful, allowing it to learn discriminative ECG characteristics and make accurate predictions across several classes. Architectural design and optimised training prepare the model for ECG signal categorization. The whole procedure is shown in the Figure 6.

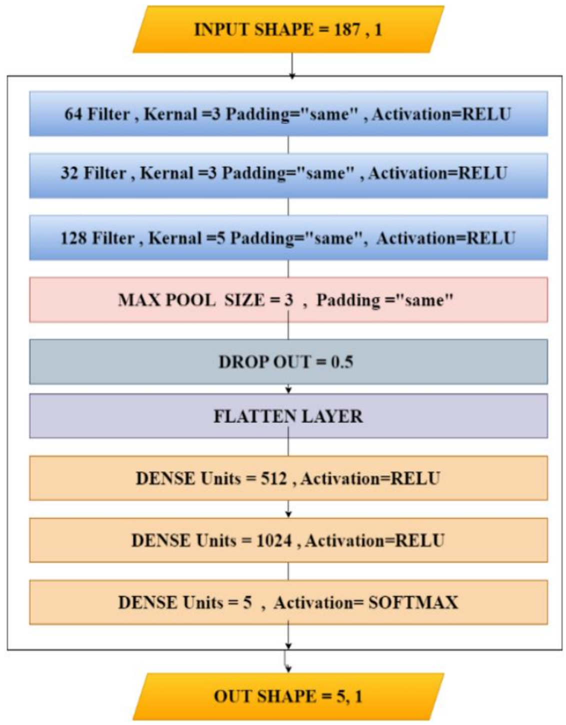

Figure 6. Proposed architecture of 1DCNN

Classification of Arrhythmias using IDCNN involves four stages: Dataset Splitting, Adding Gaussian Noise, removing noise using a Notch filter, and classification of new test ECG signals. We have discussed datasets and their processing in the section 3.

Data Segmentation**:** Here, we are classifying 27,789 ECG Beats into five classes: Normal Beats (8965), Supraventricular Beats (2779), Ventricular Beats (7236), Fusion Beats (803), and Unknown Beats (8006). We have considered all these classes for the classification. The necessary details have been included in Section 3.2.

Adding Gaussian Noise: Gaussian noise has the first benefit of having a well-behaved distribution. Noise has a sharpening effect on signals. This occurs because noise creates a different kind of shape. It's an optical illusion whereby the contrast between neighboring pixels gives the impression of more resolution than is there. Section 3.3 contains all of the relevant information.

Filter the noise using Notch filter: Electrocardiogram (ECG) detection is frequently challenged by 50-Hz interference from power lines and other devices. The 50 Hz disturbance in the ECG signal may be reduced by developing a notch filter. "To significantly speed up the process of rhythmic categorization with high accuracy, this study incorporates Gaussian noise as a preprocessing step and then applies a notch filter". Section 3.4 contains all the necessary details.

4.3 Improving classification with noise addition and filtering

The Gaussian noise addition phase used the wfdb package to load MIT-BIH Arrhythmia Database entries. With this library, we retrieved ECG signals from the specified record. We used Gaussian noise parameters like mean and standard deviation to regulate noise. The NumPy library's random. Normal function generated Gaussian noise with an ECG signal length. This noise was then added to the original ECG data to create controlled noise. This crucial phase uses wfdb for data retrieval and NumPy for noise production to establish the basis for detailed studies of how controlled noise affects ECG signals. These procedures improve ECG classification model resilience and generalisation as well as signal analysis. This Gaussian Noise addition procedure is practically shown in Figure 7 with an Abnormal Beat.

The Scipy package applies a notch filter to synthetic ECG signals after adding Gussian noise. The create_ecg_signal function generates a synthetic ECG signal first. With Gaussian noise and the sine function, this programme simulates ECG waveforms. The apply_notch_filter function addresses power line interference at 50 Hz in the produced ECG signal and is the code's main feature. The code sets a second-order bandstop filter with a notch frequency and Q using the butter function from scipy.signal. Applying the filter function to the original ECG signal using this filter creates the filtered_ecg signal. The 1DCNN model classifies arrhythmia using the filtered signals. This filtered method is practically shown in Figure 8 with an Abnormal beat.

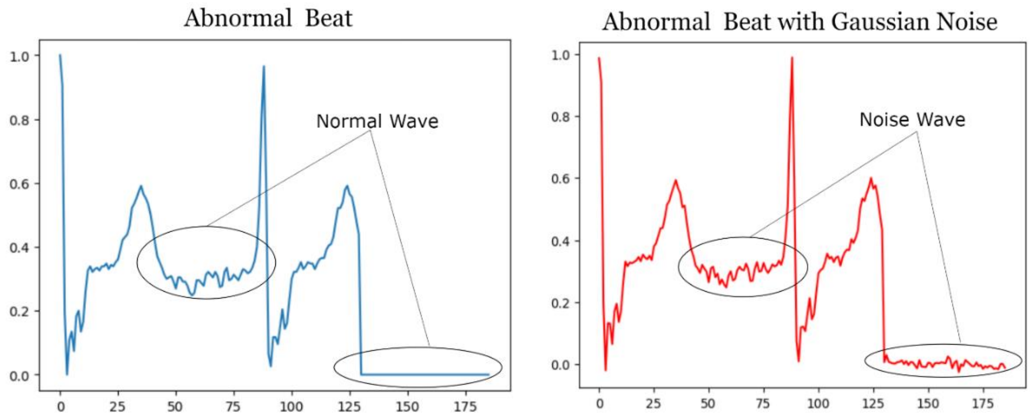

Figure 7. Normal signal to noised signal

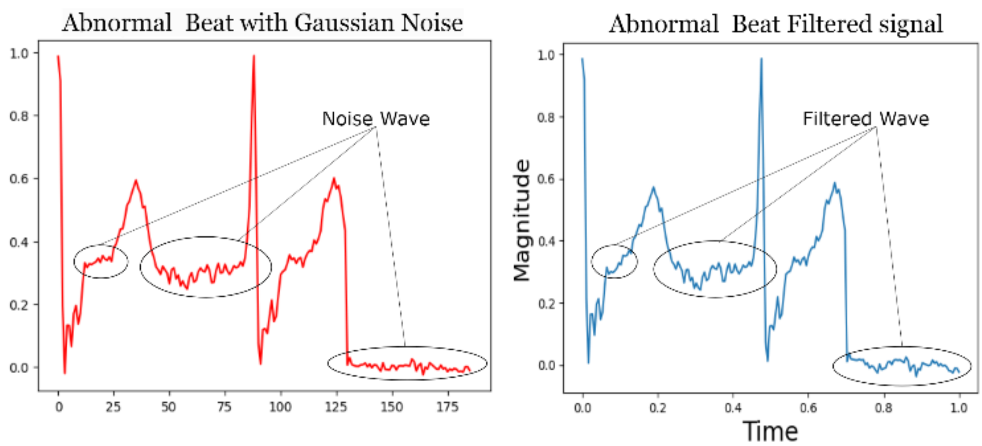

Figure 8. Noised signal to filtered signal

We have presented practically why we added Gaussian noise to the ECG data and why we used a notch filter to filter out the noise data, using the help of an abnormal signal from MITBIH. Figure 7 shows how a normal signal can be turned into noise, and Figure 8 shows how a noise signal may be turned into a filtered signal. Now that the signal has been filtered, it may be classified. When it comes to ECG signals in particular, the DCNN is ideal for categorising arrhythmias. In order to classify arrhythmias, the filtered data is fed into a 1DCNN in this manner.

5. DISCUSSION AND FINDINGS

5.1 Key performance metrics

This section gives the classification results of the Arrhythmias using IDCNN. Before examining the results, it is crucial to take into account key performance metrics, including precision, recall, F1 score, and specificity. These metrics offer a thorough assessment of the model's ability to make accurate predictions. While addressing metrics, we must understand a few crucial words connected to our model's predictions. True Positive (TP): The model accurately predicts something positive. True Negative (TN): The model appropriately predicts a negative. False Positive (FP): The model predicts a positive yet negative outcome. False Negative (FN): The model calls something negative, but it's positive. These are presented in Eqs. (1)-(4).

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + RecalP} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

The model achieved an average 99% of AC and the precision, recall, f1-score, specificity and support values are represented in the given performance matrix Table 3. In which N is Normal, S is Supraventricular, V is Ventricular, F is Fusion and Q is Unknown. Figure 9 shows a visual comparison of the important classification metrics for each class in our model.

Table 3. Performance of the proposed model

Class	Precision	Recall	F1 Score	Specificity
N	0.99	1.00	0.99	0.706
S	0.92	0.80	0.86	0.910
V	0.97	0.96	0.96	0.932
F	0.95	0.68	0.80	0.926
Q	0.99	0.99	0.99	0.408

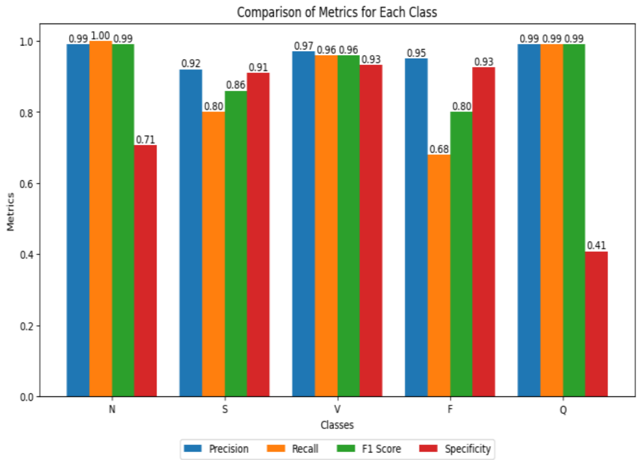

Figure 9. Comparison of metrics for each class

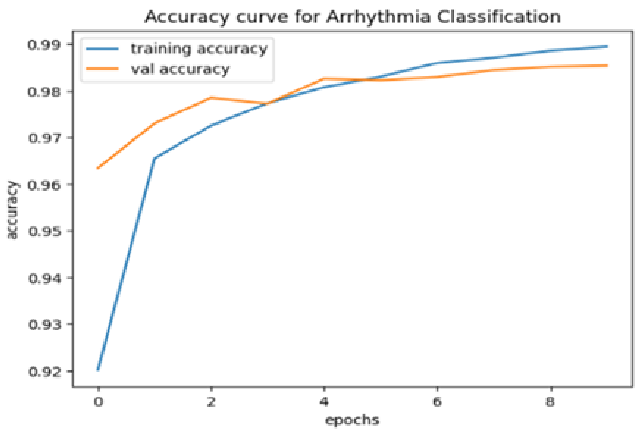

Figure 10. Accuracy curve with 1DCNN

We have simulated this classification model in 64GB RAM, 1TB SSD with 16 GB NVIDIA GTXFORCE GPU computer. In this paper, we have used 27789 ECG Beats to classify into five classifications. After classification, performance metrics: accuracy (AC), specificity (SPFTY), sensitivity (SENSTY), precision (PREN), and f1-score (F1-S) values using confusion matrices (CM) of the classification scenario. Figure10 shows the Accuracy curves for Arrhythmia classification. In this, the training accuracy is 99, and the validation accuracy is 98.6. Figure 11 shows the Loss curves for Arrhythmia classification training loss is 0.03 and validation loss is 0.05. Figure 12 shows the CM for Arrhythmia classification. In this the Normal Beat got 100%, Supraventricular Beat got 80%, Ventricular Beat got 96%, Fusion Beat got 68% and Unknown Beat got 99% classification results.

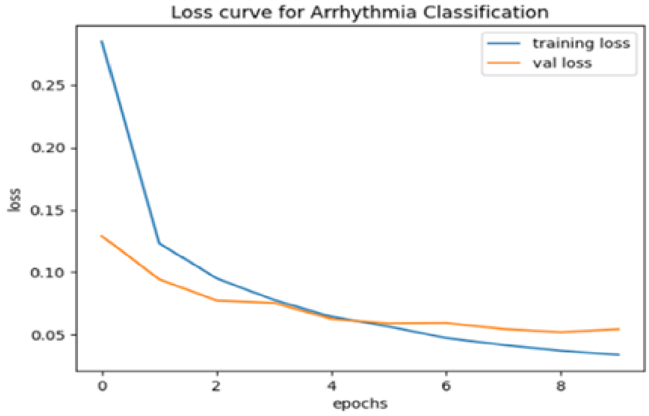

Figure 11. Loss curve with 1DCNN

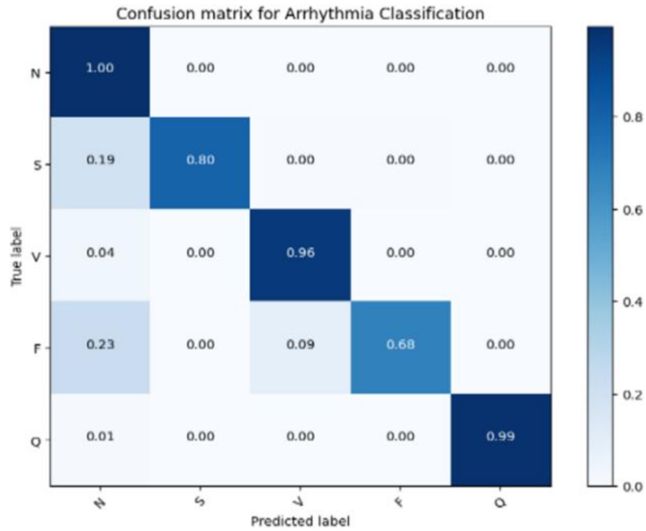

Figure 12. Confusion matrix with 1DCNN

5.2 Comparison of proposed model with previous state-of-the-art method

Arrhythmias can lead to sudden death, heart failure, or fainting, making classification difficult. Many approaches are used, including SVM, Naive Bayes, 1D-CNN, and 2D-CNN. These evaluations take time, which might lead to bad decisions. Arrhythmias are differentiated using ECG readings. Arrhythmia electrocardiograms show similar heart abnormalities due to similar symptoms. Patients receive misdiagnoses. Therefore, we proposed the 1DCNN arrhythmia classification model. Table 4 compares the proposed model to state-of-the-art models. Our model performed better in five-class classifications, according to the comparison table.

Xu et al. [45] suggested a granular sampling method and adaptive speculative mechanism (ASM) that classified three pulse types with 88.06% accuracy. Mahwish Naz et al. [46] used cubic support vector machines for deep learning to convert ECG signals into pictures with 97.6% accuracy. Bayasi's low-power ECG-based processor predicted ventricular arrhythmia with 86% accuracy [47]. In arrhythmia classification, Kumar et al. [48] used IoT-based ECG monitoring with CNN classifiers with Coyote Grey Wolf Optimisation and achieved 95% accuracy. Loh et al. [49] created a 1D-DNN Low-Cost DNN Hardware Accelerator for wearable arrhythmia detection with 78.01% accuracy. Gu et al. [50] developed a lightweight CNN hardware implementation for wearable heart rate anomaly detection with 97.69% accuracy using a 1D-CNN. Avanzato and Beritelli [51] used a 1D-CNN to diagnose ECGs with 98.33% accuracy. Acharya et al. [52] created a 9-layer deep CNN that autonomously classified five heartbeat categories with 93.47% accuracy. Yan et al. [53] used CNNs and SNNs to classify inter-patient ECGs with 90% accuracy. Eman et al. [54] compressed signals with BERT, reducing storage by 83% and maintaining 92.41% accuracy. Yin et al. [55] used 1D-CNN and DGCCA to diagnose tool wear with 95.6% accuracy. Deep learning was used to detect deadly arrhythmia in FECG signals by Nakatani et al. [56] with 96.2% accuracy. Ting et al. [57] used CNN to detect fatal ECGs from abdomen recordings with 95.2% accuracy. Wang et al. [58] developed a CNN with NCBAM for automated ECG heartbeat categorization with 68.76% accuracy. Wu et al. [59] used 2D-CNNs to classify ECG signals with 98% accuracy.

Table 4. An evaluation of the suggested model against state-of-the-art approaches

Reference	Year	Classes	Approaches	Dataset	Performance
[45]	2018	3	SVM (ASM)	MITBIH	88.06%
[46]	2021	5	Cubic SVM	MITBIH	97.6%
[47]	2015	2	Navie Bayes	MITBIH	86%
[48]	2022	5	Coy-GWO Deep CNN	MITBIH	95%
[49]	2020	5	DNN	MITBIH	78.01%
[50]	2023	5	1D-CNN	MITBIH	97.69%
[51]	2020	3	1D-CNN	MITBIH	98.33%
[52]	2017	5	9 Layer DCNN	MITBIH	94.03%
[53]	2021	5	SNN	MITBIH	90%
[54]	2022	4	BERT	MITBIH	92.41%
[55]	2022	4	1D-CNN+ DGCCA	MITBIH	95.6%
[56]	2021	2	CNN with FECG	MITBIH	96.2%
[57]	2021	2	2D-CNN with FECG	MITBIH	95.2%
[58]	2021	4	2D-CNN + NCBAM	MITBIH	68.76%
[59]	2018	3	2D-CNN	MITBIH	98%
Proposed	**2024**	**5**	**1D-CNN with Notch**	MITBIH	**99%**

5.3 Statistically significant improvements in proposed work over previous work

The results of this investigation demonstrate statistically significant improvements in the proposed approach when compared to earlier approaches. The statistical analysis supports these findings by demonstrating a significant improvement and substantial variations in important performance measures. Within our study, we apply statistical significance tests, such as t-tests, to measure the extent of enhancements compared to previous research by utilizing error rates as a parameter.

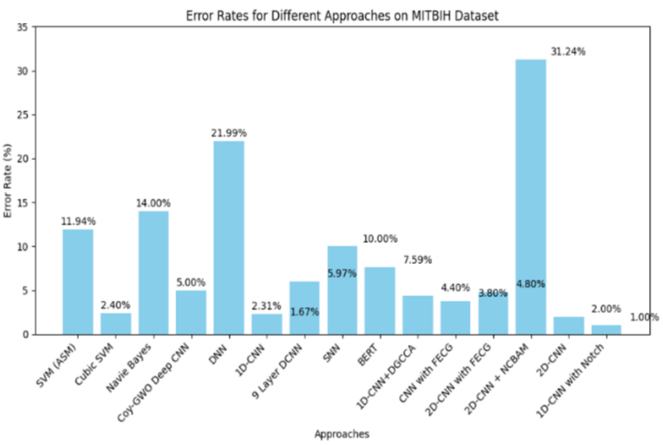

Figure 13. Error rates for different approaches

This method allows a careful examination of the importance of observed differences in error rates, giving useful information on how well the proposed model works compared to earlier methods. Figure 13 visually represents these statistical analyses, offering a graphical depiction of the observed improvements in error rates.

6. CONCLUSIONS

In order to remove noise from ECG signals, the study uses a Notch filter and Gaussian noise modeling to present a unique diagnostic paradigm for arrhythmia categorization. There are five different types of arrhythmias: fusion (F), ventricular (V), supraventricular (S), normal (N), and unknown (Q). With the use of a modified 1D CNN, the classification system was able to obtain impressive accuracy rates: 86% for supraventricular, 96% for ventricular, 80% for fusion, and 99% for unknown arrhythmias. The classification system's overall error rate is just 1%.

This high accuracy points to the system's dependability and qualifies it for practical use in the clinical evaluation of patients with arrhythmias. The system's ability to provide prompt and precise diagnoses helps doctors, hospitals, and healthcare facilities make wise decisions.

The paper looks ahead, outlining planned research to expand the network and investigate its capacity to find features relevant to various ECG datasets. Adding more physiological signals, such as PPG, is believed to enhance the system's functionality. To enhance performance even more and address potential constraints, it is advisable to test different designs and approaches. The study recognizes that validation efforts are still necessary to guarantee the suggested diagnostic framework's clinical acceptance.

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NOMENCLATURE

N	Normal
S	Supraventricular
V	Ventricular
F	Fusion
Q	Unknown

Greek symbols

v	Signal frequency (Hz)
A	Signal amplitude
σ	Sinusoidal signal
π	Probability Density Function (PDF)
μ	Mean of signal Noise
v_{Noise}	Noise frequency (Hz)
$A_{SignaNoise}$	Noise amplitude

Subscripts

Noise	Pertaining to noise signals
signal Noise	Combined signal and noise