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ECG Arrhythmia Measurement and Classification for Portable Monitoring

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Abstract: Globally, cardiovascular disease kills more than 500000 people every year, thus becoming the primary reason for death. Nevertheless, cardiovascular health monitoring is essential for accurate analysis and therapy of heart disease. In this work, a novel deep learning-based StrIppeD NAS-Network (SID-NASNet) for arrhythmia categorization into octa-classes with electrocardiogram (ECG) signals is presented. First, the ECG signals are recorded in real time using 12-lead electrodes. Then, the Discrete Wavelet Transform (DWT) is used to denoise the signals to reduce repetition and increase resilience. The noise-free ECG signals are fed into a K-means clustering algorithm to group ECG signal segments into a set number of clusters to identify patterns that may indicate heart abnormalities. Subsequently, the deep learning-based NASNet with Stripped convolutional layers is used to detect ECG irregularities of arrhythmia. Each sample point is examined for its local fractal dimension before extracting the heartbeat waveforms within a predetermined window length. A bio-inspired Dingo Optimization (DO) algorithm is used in the SID-NASNet to normalize the parameters to improve the efficiency of the network with low network complexity. The efficiency of the proposed SID-NASNet is assessed with specificity, accuracy, precision, F1 score and recall based on the MIT-BIH arrhythmia dataset. From the test results, the proposed SID-NASNet achieves an accuracy of 98.22% for effective categorization of ECG signals. The proposed SID-NASNet improves the overall accuracy of 1.24%, 3.76%, 1.87%, and 0.22% better than ECG-NET, Deep Learning (DL)-based GAN, 1D-CNN, and GAN-Long-Short Term Memory (LSTM), respectively.

Keywords: ECG signal, arrhythmia classification, deep learning, discrete wavelet transform, stripped convolution, Dingo optimization algorithm.

1. INTRODUCTION

Recently, the landscape of cardiac health monitoring has undergone a transformative evolution, particularly in the area of electrocardiogram (ECG) technology [1]. With the surge in portable monitoring devices, an urgent need for accurate, reliable, and real-time detection and classification of arrhythmias has emerged [2]. The monitoring of vital signals is essential in smart medical devices such as the ECG [3], photoplethysmogram (PPG) [4], and electroencephalogram (EEG) [5]. Recent Machine Learning (ML) and Deep Learning (DL) approaches have advanced the landscape of ECG-based arrhythmia detection. Sophisticated algorithms can analyze ECG signals with unprecedented accuracy and distinguish between normal sinus rhythms and different arrhythmic conditions [6]. The process of categorizing ECG data into distinct illness classes is a challenge for pattern recognition. Highly accurate computerized ECG classification could be a cost-effective mass screening method for cardiac problems [7], [8].

Several techniques have been described for the identification of cardiac arrhythmias, including heart-rate inconsistency, spectral inspection, progressive frequency distribution, and nonlinear signal processing approaches [9], [10]. These techniques typically analyze three basic components: P-wave, T-wave, and Q-wave, R-wave and S-wave (QRS) complex, as shown in Fig. 1. In recent days, deep learning techniques, particularly neural networks such as Deep Neural Network (DNN) [11], Long-Short Term Memory (LSTM) [12], You Only Look Once (YOLO) [13] and so on with multiple layers, have revolutionized various fields by enabling machines to learn intricate patterns from vast amounts of data. In order to properly treat heart diseases,

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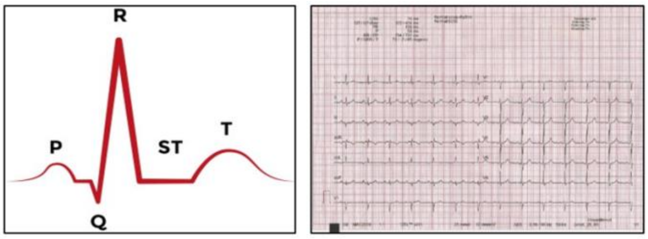
the system must function consistently in everyday situations, which means that the monitor should not interfere with people's comfort and daily activities. Sometimes, some ECG arrhythmia classification algorithms may misclassify an arrhythmia as a normal rhythm or vice versa [14], [15]. This could pose challenges for healthcare providers tasked with interpreting ECG results, which is important for potentially irrelevant treatments due to false positives or false negatives [16].



(a) (b)

Fig. 1. (a) Characteristics of the ECG signal, (b) Regular ECG sheet samples.

In this area, we focus on the development of precise and efficient arrhythmia classification using deep learning methods, drawing inspiration from such scenarios [17]. The proposed method for classifying ECG signals with cardiac arrhythmias can be applied in various critical areas such as clinical diagnosis, remote patient monitoring, and emergency response. It improves the accuracy in detecting abnormal heart rhythms to enable timely medical interventions. This approach supports the development of advanced wearable technology for continuous heart monitoring. The main contributions of the research work can be summarized as follows:

- In the present study, a novel StrIppeD NAS-Network (SID-NASNet) is presented to identify abnormal rhythms in ECG signals.
- The first step is to record ECG data in real time using 12-lead electrodes, and denoising these signals with Discrete Wavelet Transform (DWT) removes noise artifacts.
- The noise-free ECG signals are fed into a K-means clustering algorithm to group ECG signal segments into a set number of clusters to detect patterns that may indicate heart abnormalities.
- DL-based NASNet with Stripped convolutional layers to detect ECG irregularities in cardiac arrhythmias.
- A bio-inspired Dingo Optimization (DO) algorithm is used in the SID-NASNet to normalize the parameters to improve the efficiency of the network with low network complexity.

The remaining paper have been divided into the five classes listed below. Section 2 summarizes the literature review; Section 3 presents the SID-NASNet to categorize the octa-classes of arrhythmias from ECG signals; Section 4 presents the results and discussion; and Section 5 contains the conclusion and future work.

2. LITERATURE OVERVIEW

Recently, researchers have presented numerous ways to classify ECG signals to treat arrhythmias. A summary of various recent ML and DL studies to categorize different arrhythmia signals is given in this section.

In 2023, Roy et al. [18] designed ECG-NET with a deep LSTM auto-encoder to detect irregularities using ECG signals. The encoder component condenses the ECG data into a latent space model with a reduced size, while the decoder component endeavors to reconstruct the original ECG signal. Using the frequency distribution of these reconstruction losses, a threshold value for anomalous reconstruction losses is determined. This model was used on openly accessible ECG-5000 dataset with the highest accuracy of 98.0% for anomaly detection.

In 2023, Qin et al. [19] developed a DL-based GAN for ECG irregularity detection based on one-class classification. The discriminator used a mini-batch discrimination training technique to generate ECG signals. This involved integrating a Bi-LSTM layer into a GAN framework. The aim was to develop a robust anomaly detector capable of accurately identifying deviations. The results obtained with this technique achieve an accuracy of 95.05% in the MIT-BIH arrhythmia dataset.

In 2023, Wang et al. [20] presented a DL approach for ECG signal processing using a two-tiered hierarchical deep learning architecture with GAN. The initial model, known as Memory-Augmented Deep AutoEncoder with GAN (MadeGAN), was developed for differentiating irregular signals from regular ECG signals. In the evaluation of the proposed method, ECG signals from the MIT-BIH dataset were used to demonstrate its effectiveness.

In 2022, Chen et al. [21] designed an automated framework adept at discerning between normal and abnormal ECG readings. This approach introduces a DNN model equipped with multiple channels and scales, providing an end-to-end framework to categorize ECG signals without the need for feature extraction. Experimental results show that the method can distinguish between normal and pathological ECG signals and achieves high identification rates.

In 2021, Ullah et al. [22] presented an efficient technique for precise categorization of the ECG signals. For this model, a 1D-CNN architecture was developed that includes a Fully-Connected (FC) layer, two downsampling layers, and two convolutional layers. In this model, the 1D data is converted into 2D images, resulting in improved classification accuracy. Subsequently, a 2D-CNN was used, which includes three 2D convolutional layers, three downsampling layers, one input layer, one output layer, and one FC layer. The proposed 1D and 2D architectures achieved impressive accuracies of 97.38% and 99.02%, respectively.

In 2021, Lai et al. [23] developed a DL architecture that includes three key stages: feature extraction, ECG-lead subset selection, and decision-making for comprehensive evaluation of various common types of ECG abnormalities. The ECG-lead subset selection unit was integrated into the architecture to effectively streamline complexity. This module pinpointed leads II, aVR, V1, and V4 as the optimal 4-lead ECG subset. In both the training and test datasets, the architecture using this 4-lead subset showed significant improvement over the architecture using the entire 12-lead ECG.

In 2022, Jamil and Rahman [24] presented a DL technique to categorize ECG data into 16 types of arrhythmias. They used Continuous Wavelet Transform (CWT) to convert filtered ECG data into a 2D signal. DCNN was integrated into the attention unit and then provided a time-frequency domain representation of the CWT, extracting a Spatial Feature Vector (SFV). The proposed model achieved 99.84% accuracy with a Reduced Feature Vector (RFV) for arrhythmia classification using k-fold cross-validation.

In 2021, Rath et al. [25] developed the ECG samples used as essential inputs for the HD detection model. To improve HD detection, DL and ML structures were recognized and relevant classification models were developed and evaluated. The GAN framework aimed to address imbalanced data by creating and utilizing more synthetic data for recognition. GAN-LSTM achieved a peak accuracy of 0.992 compared to alternative models, as shown by the simulation results using the standard MIT-BIH dataset.

In 2020, Hwang et al. [26] presented a YOLO-based arrhythmia detection structure that continuously detects every heartbeat and classifies irregular rhythms from extended ECG recordings. The model replaces bounding boxes with a bounding window and uses a 1D-CNN instead of a 2D-CNN using raw ECG signals. The variable lengths of the bounding window allow the model to predict different arrhythmias and regulate the optimal size of the heartbeat window for detection. However, the model's accuracy decreases due to its dependence on the attention unit.

In 2020, Atal and Singh [27] developed an optimization-based deep CNN system for automatic categorization of cardiac abnormalities. The Bat-Rider Optimization Algorithm (BaROA) was created by combining the MOBA and ROA techniques. This BaROA-based DCNN classifier was used to classify ECG signals as either exhibiting arrhythmia or not. Despite the initial low accuracy, an accuracy of 93.19 was achieved when tested on the MIT-BIH dataset.

The literature overview shows that the extraction and categorization of physical features is very labor-intensive, which reduces the effectiveness of current methods. Arrhythmias, from common types such as atrial fibrillation to complex arrhythmias, pose challenges due to sporadic or subtle ECG changes, especially with noisy recordings. Recognizing diverse ECG patterns for different arrhythmias is a formidable task for deep learning algorithms. To overcome these challenges, an automatic signal decomposition and classification model was developed to classify the octa-arrhythmia cases using ECG signals.

3. PROPOSED METHOD

In this work, a novel SID-NASNet is developed for effective categorization of ECG signals for the identification of octa-arrhythmia cases. The schematic representation of the proposed method is shown in Fig. 2. The ECG signals are compiled from the MIT-BIH dataset and denoised using DWT to eliminate the noisy artifacts. The K-means clustering technique was applied to cluster similar segments of the signal together to identify cardiac abnormalities. The clustered ECG signals are fed to the DO SID-NASNet with Stripped convolutional layers to detect the octad classes of ECG arrhythmias.

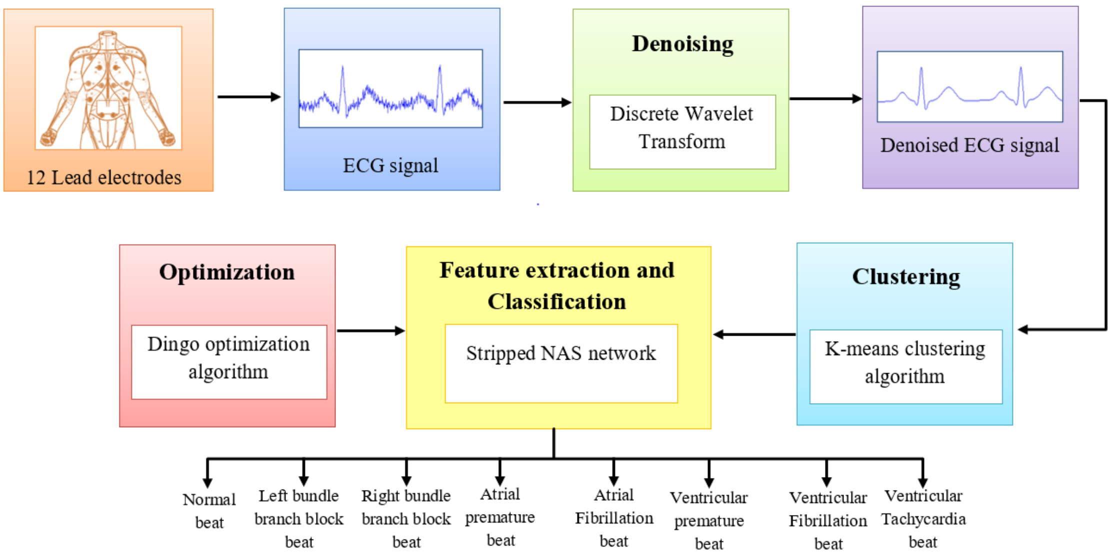


Fig. 2. The overall schematic depiction of the proposed model.

A. *MIT-BIH Arrhythmia Database*

In this research, the MIT-BIH arrhythmia dataset available from the PhysioNet website is used [28]. There are octa beats such as 2316 Normal beats (N), 219 Left Bundle branch blocks (LB), 240 Right Bundle branch block beats (RB), 45 Atrial Premature beats (AP), 171 Ventricular Premature beats (VP), 315 Atrial Fibrillation beats (AF), 127 Ventricular Fibrillation beats (VF), and 628 Ventricular Tachycardia beats (VT). At a sampling frequency of 360 Hz, two leads were used to collect information. The proposed method divides the ECG signal into 200 sampling components. Fixed-length frames were used to retrieve the ECG waves around the largest peak of the R-R interval. In this dataset, arrhythmias are categorized into 8 groups, and the corresponding number of beats for each class is shown in Table 1.

Table 1. Description of MIT-BIH database for octa-classes.

Class number	Classes	Number of segments
0	N	2316
1	RB	240
2	LB	219
3	VP	171
4	AP	45

QRS duration calculation: QRS boundaries are determined by comparing the raw heartbeats with the start and end of each QRS. As a result, the determination of the QRS boundaries coincides with the acquisition of the ECG signals. The chest-ECG QRS duration is predicted at a location on the body other than the chest. Cardiac ECG QRS duration values are obtained by calibrating the chest-ECG QRS period estimates. The proposed method can be fairly well regulated by learning the bias using simple linear regression.

B. Discrete Wavelet Transform (DWT)

The DWT [29] is used for ECG signal processing, including the evaluation of ECG signals. It decomposes a signal into different frequency components, revealing both time and frequency information. The DWT decomposes the ECG signal $x(n)$ into approximation coefficients A and aspect coefficients D on different scales or levels. The decomposition is usually performed iteratively, resulting in several levels of approximation and detail coefficients. The number of levels depends on the selected wavelet and the desired resolution. Equation (1) is used to obtain the approximation coefficients A and the detail coefficients D at level j:

$$A(k) = \sum_n x(n) \times p(2k - n) \tag{1}$$

$$D(k) = \sum_n x(n) \times q(2k - n) \tag{2}$$

where $p(n)$ and $q(n)$ are the low-pass and high-pass filter coefficients associated with the selected wavelet, respectively, $x(n)$ is the ECG input signal, $A(k)$ and $D(k)$ are the approximation and detail coefficients at level k, respectively. The DWT breaks down the signal into different resolutions, where each pixel shows a previous approximation detail from the previous resolution, thus capturing the depth and approximation characteristics.

C. K-means clustering algorithm

The K-means clustering algorithm [30] is used to group data-points into a predetermined number of clusters in the context of analyzing ECG signal to detect cardiac abnormalities. K-means clustering is used to group similar segments of the signal to potentially identify patterns indicative of cardiac abnormalities. The K-means method begins by arbitrarily selecting K centroids in the feature space to form the initial clusters. Each data point is assigned to its adjacent centroid and grouped accordingly. Convergence occurs when also a set number of iterations is reached or when the centroids stabilize. K-means aims to reduce the sum of squared distances between the data points and their centroids, effectively dividing the data into K clusters. Mathematically, the objective function C is defined as:

$$C = \sum_{i=1}^{K} \sum_{x \in C_i} ||x - \mu_i||^2 \tag{3}$$

where K refers to the number of clusters, C_i represents the data-points assigned to cluster i, μ_i is the centroid of cluster i, and $||x - \mu_i||^2$ denotes the squared Euclidean distance between data-point x and centroid μ_i. In the context of ECG signal analysis, the features used for clustering can be derived from various features of the signal such as amplitude, frequency, and waveform morphology. To set the parameters of the K-means algorithm for abnormality detection in ECG signals. Typically, the number of clusters (K) is set to 2. Set the number of clusters to 15 to ensure robustness and avoid poor local minima. Select a high value of 300 to ensure convergence. Normalize the data using Standard Scaler to handle different magnitudes in the ECG signals. After clustering, the segments of the ECG signal belonging to the same cluster will have similar patterns that can be further analyzed to detect cardiac abnormalities or arrhythmias.

D. StrIppeD NAS-Network (SID-NASNet)

The deep learning-based SID-NASNet was developed for ECG classification and usually consists of Stripped convolutional layers followed by pooling and FC layers. Stripped convolutional layers use a series of 1D convolutional filters with the ECG input signal. Each filter passes through the signal to extract local patterns and capture relevant features at different temporal scales. The output of a 1D convolutional layer at position i was calculated as follows:

$$Z(i) = \sum_{j}^{f-1} x(i + j) \times w\,(j) + b \tag{4}$$

where $S(i)$ refers to the result at position i, $x(i + j)$ is the input signal at position $i + j$, $w(j)$ is the weight of the convolutional filter at position j, b is the bias term, and f is the size of the convolutional filter. The NASNet [31] effectively extracted relevant temporal features from ECG signals while maintaining computational efficiency by using Stripped convolutional layers [32]. After the Stripped convolutional layers, the maxpool layers are used for downsampling the feature maps by reducing their spatial dimensionality while preserving the important features. The output of a maxpooling operation at position i is estimated as

$$Z(i) = \max\,(x(i \times s{:}\,(i + 1) \times s)) \tag{5}$$

where $x(i \times s{:}\,(i + 1) \times s)$ represents the input signal slice over which pooling is performed, and s is the size of the pooling window. The output of each convolutional layer consists of multiple feature maps, each capturing different aspects of the input signal. These feature maps represent higher-level representations of the ECG input signal. Fig. 3 shows the proposed SID-NASNet for efficient ECG categorization. In the NASNet, the FC layers are replaced by a global pooling layer succeeded by a SoftMax layer for ECG signal classification. The global average pooling summarizes the spatial features of all channels in a single vector.

$$Z(i) = \frac{1}{N}\sum_{j=1}^{N} x(j) \tag{6}$$

where N is the number of elements. The SoftMax layer converts the aggregated features into class probabilities.

$$P(Z = i) = \frac{e^{L_i}}{\sum_{j=1}^{C} e^{L_i}} \tag{7}$$

where L_i is the logit for class i and C refers to the number of classes. By adapting NASNet in this manner, we can effectively utilize its architecture for ECG signal classification tasks by capturing relevant temporal features for accurate classification. During training, a definite cross-entropy loss function was used to measure the change between the predicted and true class prospects, which facilitates the optimization of the network's parameters.

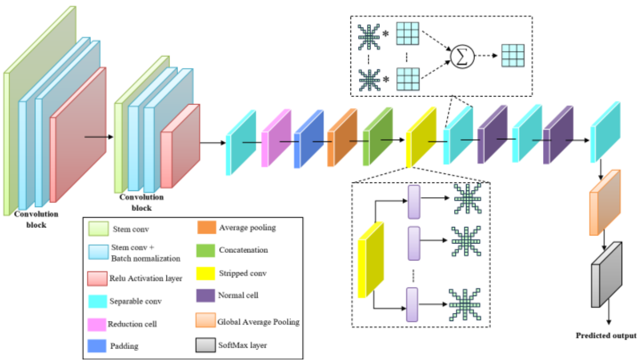


Fig. 3. Architecture of the proposed Stripped NAS-Network.

E. Dingo optimization algorithm

The DO algorithm [33] is a metaheuristic technique inspired by the hunting behavior of dingoes. This algorithm aims to optimize parameters such as weights and biases of the NASNet for ECG signal classification to detect cardiac abnormalities. This algorithm has three strategies for tracking, organization strategies and scavenging behavior are attack options. Initialize the search agent, set the maximum number of iterations i, the inertia weight, and the learning factor. This behavior is represented as

$$d_i(s+1) = \beta_1 \sum_{j=1}^{a} \frac{[\varphi_i(s) - d_i(s)]}{a} - d_*(s) \tag{8}$$

where $d_i(s+1)$ refers to the new location of the search agent, a denotes the arbitrary number generated in the interval {2, sizePop/2}, where sizePop refers to the total population, $\varphi_i(s)$ is the subset of dingoes where $\varphi \in$D, $d_i(s)$ is the present dingo, $d_*(s)$ is the finest dingo found in the previous iteration, α refers to the arbitrary number generated uniformly between the interval [-0.5, 0.5]. Next, initialize the hectic search agent and randomly generate the D-dimensional vector where each component has a value between 0 and 1 and it is expressed as

$$d_i(s+1) = d_*(s) + \beta_1 * e^{\beta_2} * (d_x(s) - d_i(s)) \tag{9}$$

where β_1 refers to the random number in the range of [-2, 2], β_2 refers to the random number generated consistently in the range of [-0.5, 0.5], x is the arbitrary number generated in the interval from 1 to the size of the maximum search agent, and $d_x(s)$ are the x dingoes selected where $i \neq x$. This is expressed as

$$d_i(s+1) = \frac{1}{2}[e^{\beta_2} * d_x(s) - (-1)^{\sigma} * d_i(s)] \tag{10}$$

where x is the arbitrary number generated in the range from 1 to the size of the maximum search agent and $d_x(s)$ is the x dingo selected where $i \neq x$ and σ is the generated arbitrarily binary number $\sigma \in \{0,1\}$. Then calculate the search agent's fitness value and derive it as

$$SR(i) = \frac{fitness(\max) - fitness(i)}{fitness(\max) - fitness(min)} \tag{11}$$

where $fitness(max)$ and $fitness(min)$ are the best and worst fitness ratios in the current generation and $fitness(i)$ defines the current fitness value of the i-th dingo. The low survival rate is expressed as

$$d_i(s) = d_*(s) + \frac{1}{2}[d_x(s) - (-1)^{\sigma} * d_y(s)] \tag{12}$$

Here, $d_i(s)$ is the update of the search agents with low survival rate, d_x and d_y are the arbitrary numbers created in the interval from 1 to the maximum size of the dingoes, $d_*(s)$ is the best search agent found in the previous phase, and σ is a random variable for the addition or subtraction of vectors. Exit the program when the condition is met to obtain the optimal results.

4. RESULTS AND DISCUSSION

In this section, we present the results of our work and analyze their implications. The results are discussed in detail, highlighting the main findings of our proposed approach. The obtained results are compared with previous research to demonstrate the competence of the proposed approach. Finally, we address the potential and areas for future research. This comprehensive discussion provides a thorough understanding of the implications of the proposed approach.

A. Experimental results of the proposed model

In this section, the experimental results of the proposed SID-NASNet model for ECG signal classification are presented. The significant improvements in classification accuracy were observed across multiple ECG signals for octa-arrhythmia categories using the proposed SID-NASNet model.

The experimental results of the proposed SID-NASNet model on a sample of eight different ECG signals are shown in Fig. 4. The ECG signals are processed by portioning the specific region from the ECG sheets, as shown in column 1. The segmented ECG images are shown in column 2 after DWT denoising has removed the distortions. These ECG signals are denoised and provided to the NASNet as output for the detection of rhythm abnormalities, especially class 0 and 7.

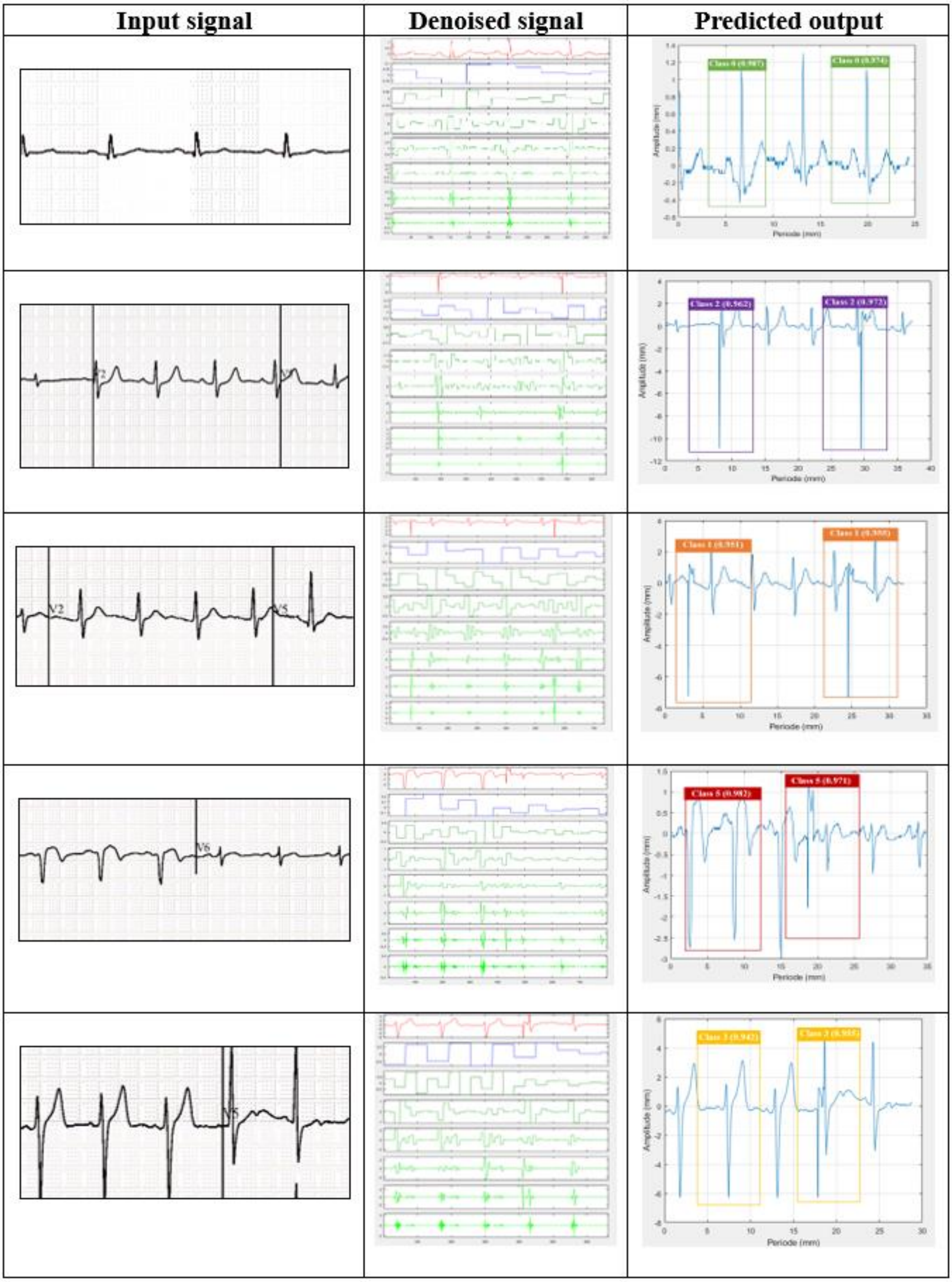


Fig. 4. Experimental fallouts of the proposed SID-NASNet model.

B. Simulation details and metrics

The experimental setup of the research was carried out using MatLab 2020b on a Windows 10 PC with an Intel i5 2.10 GHz processor and 8GB RAM. The evaluation of the proposed SID-NASNet involved analyzing various metrics including network metrics derived from the collected dataset. The evaluation metrics such as ACcuracy (AC), PRecision (PR), SPecificity (SP), REcall (RE), and F1-score (F1) are used to determine the effectiveness of the proposed SID-NASNet in classifying arrhythmia cases.

$$SP = \frac{T_{neg}}{T_{neg}+F_{pos}} \quad (13)$$

$$PR = \frac{T_{pos}}{T_{pos}+F_{pos}} \quad (14)$$

$$RE = \frac{T_{pos}}{T_{pos}+F_{neg}} \quad (15)$$

$$AC = \frac{T_{pos}+T_{neg}}{Total\ no.of\ samples} \quad (16)$$

$$F1 = 2\left(\frac{PR*RE}{PR+RE}\right) \quad (17)$$

where T_{pos} and T_{neg} signify true positives and true negatives, F_{pos} and F_{neg} denote false negatives and false positives of the ECG signals. In this experimental study, the proposed SID-NASNet model was evaluated using the MIT-BIH database, which is divided into 25% for testing and 75% for training.

SID-NASNet model performance scrutiny

The performance of the proposed SID-NASNet model was measured in terms of the AC, SP, RE, PR, and F1 score. These metrics were used to evaluate its competence. The analysis included true positives and true negatives as well as false positives and false negatives derived from sample data and signals. Performance evaluation was performed on eight sample images using these parameters. The proposed SID-NASNet model showed high efficiency in detecting various arrhythmias and distinguished irregular beats from normal ones (N). The representation in Table 2 confirms its efficiency with an accuracy of 98.22% for the dataset. It also achieved an overall SP, F1, PR, and RE of 96.92%, 96.97%, 97.07%, and 96.95%, respectively.

Table 2. Efficiency evaluation of the proposed method.

Classes	AC	SP	F1	PR	RE
0	99.05	97.02	97.87	98.25	98.26
1	98.28	98.25	98.26	98.03	97.02
2	98.04	97.24	98.25	96.21	97.84
3	98.25	96.21	97.84	98.26	97.14
4	99.04	98.35	96.03	98.36	97.04
5	98.23	95.05	96.04	96.16	96.02
6	97.25	97.02	95.48	96.11	95.23
7	97.62	96.22	96.04	95.21	97.12
Average	98.22	96.92	96.97	97.07	96.95

Fig. 5 illustrates the efficiency metrics of the proposed SID-NASNet for each arrhythmia type. The results show that the proposed SID-NASNet achieved an accuracy of 98.22%, a precision of 97.07%, and a recall of 96.95% in classifying the five different types of arrhythmias. It is noteworthy that the recall is comparatively lower, which may be due to the limited dataset for AP compared to other arrhythmia types. Furthermore, AP provides beat-to-beat features in addition to morphologic features. The SID-NASNet model detects 10 s ECG segments in just 0.02 s, enabling real-time application for effective identification of ECG abnormalities.

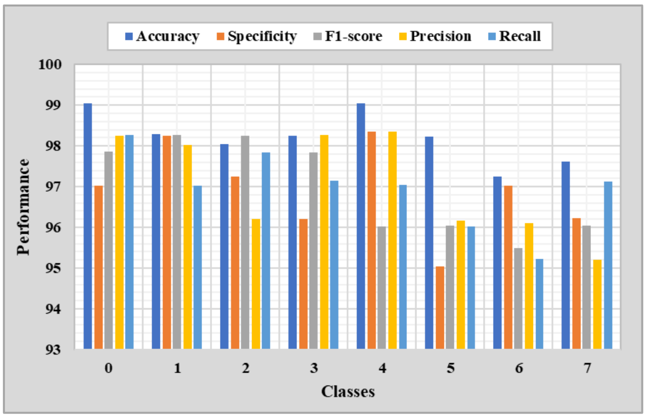


Fig. 5. Performance assessment of the proposed SID-NASNet.

Accuracy and loss evaluation

In this sub-section, the performance of the proposed SID-NASNet is evaluated using metrics such as accuracy, which captures the predictive ability of the model, and loss functions to quantify the discrepancy between predicted and actual values.

Fig. 6 shows the accuracy graph, with the number of epochs on the x-axis and the accuracy values on the y-axis. Fig. 6 shows that the loss of the proposed SID-NASNet model decreases as the number of epochs increases. This shows that the SID-NASNet achieves high classification accuracy for arrhythmias.

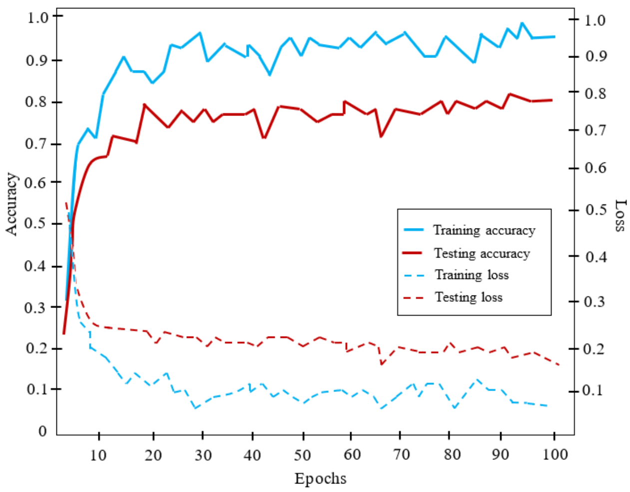


Fig. 6. Accuracy and loss graph of the proposed SID-NASNet.

Classification ROC analysis

The performance of the proposed ECG arrhythmia classification model is evaluated with Receiver Operating Characteristic (ROC) analysis by plotting the true positive rate against the false positive rate.

Fig. 7 shows the ROC curve of the proposed SID-NASNet classification model for eight different classes (Class 0 to Class 7). The ROC curves for each class with their respective Area Under ROC Curve (AUC) values range from 0.963 to 0.985. Fig. 7 shows that Class 6 has the highest AUC value (0.985), while Class 7 has the lowest AUC value (0.963). Moreover, the proposed SID-NASNet uses fewer parameters, which keeps the efficiency high while reducing the complexity. The proposed SID-NASNet uses a limited number of GFLOPs to demonstrate its efficiency. Furthermore, the classification procedure for an ECG signal with 7.2 GFLOPS takes 102 ms. In the proposed SID-NASNet, fewer parameters are used to achieve higher accuracy, which reduces the complexity based on GFLOPS and CPU/GPU runtime.

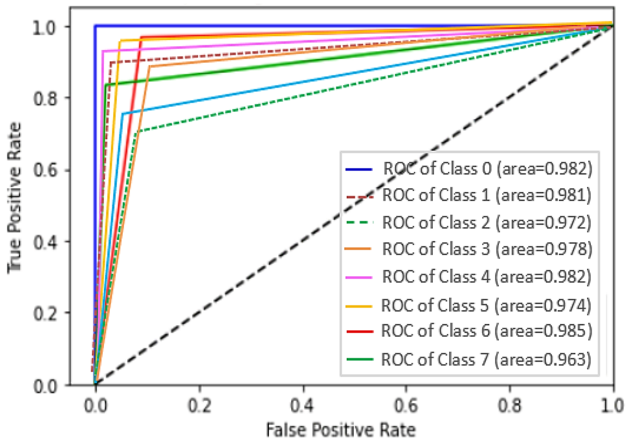


Fig. 7. ROC curve of the proposed SID-NASNet.

C. *Comparison scrutiny*

The efficiency of conventional networks was measured to validate the performance gains achieved by the proposed NASNet in reaching high accuracy. In this evaluation, NASNet was compared with established models such as AlexNet, DenseNet, and LeNet.

Table 3 shows a comparison of various conventional DL networks based on their maximum classification accuracy. In contrast to NASNet, the conventional DL networks did not show better results. Using the provided network metrics, this comparative evaluation was performed, revealing the superior performance of NASNet compared to other detection networks. Specifically, compared to AlexNet, DenseNet, and LeNet, NASNet improves the overall accuracy by 3.11%, 2.11%, and 1.19%, respectively.

Table 3. Comparison of various traditional networks.

Networks	SP	PR	RE	AC	F1
AlexNet	89.27	87.11	85.51	95.16	94.02
DenseNet	90.15	88.62	89.25	96.14	95.24
LeNet	88.05	86.13	85.54	97.05	96.12
NASNet	96.92	97.07	96.95	98.22	96.97

Table 4 compares different techniques for detecting abnormalities in ECG signals and their respective accuracies. ECG-NET technique [18] has an accuracy of 98.0%, DL-based GAN [19] achieving 95.5% accuracy, and 1D-CNN [22] an accuracy of 97.38%. The proposed SID-NASNet method outperforms all the listed techniques with a highest accuracy of 98.22%. The proposed SID-NASNet increases the overall accuracy by 0.22%, 2.76%, and 0.85% better than ECG-NET [18], DL-based GAN [19], and 1D-CNN [22], respectively. However, the previous networks did not perform better than the projected SID-NASNet. Table 4 shows that the SID-NASNet model outperforms the other approaches.

Table 4. Accuracy analysis of the proposed method with prior techniques.

Authors	Methods	Accuracy [%]
Roy et al. [18] (2023)	ECG-NET	98.00
Qin et al. [19] (2023)	DL-based GAN	95.50
Ullah et al. [22] (2021)	1D-CNN	97.38
Proposed	SID-NASNet	98.22

Table 5 compares the efficiency of the proposed SID-NASNet with different ECG signal datasets with precision, recall and accuracy for arrhythmia classification. The PTB Diagnostic ECG Database [34] achieved 96.13% accuracy, but suffers from the limited diversity of its patient population. The PhysioNet Database [35] reported 97.05% accuracy, which may be affected by noise in the real-world data. The Long-Term AF Database [36] has an accuracy of 97.32%, although its long-term records could lead to variability. The proposed SID-NASNet achieves an accuracy of 98.22% with the MIT-BIH Arrhythmia dataset, which is comparatively higher than the existing [34], [35], and [36] datasets. From this analysis, the proposed SID-NASNet has a high accuracy on the MIT-BIH arrhythmia database, but does not perform better on the other datasets.

Table 5. Efficiency of the proposed SID-NASNet for various datasets.

Datasets	Precision [%]	Recall [%]	Accuracy [%]
PTB Diagnostic ECG DB	95.22	95.54	96.13
PhysioNet DB	94.13	96.21	97.05
Long-Term AF DB	95.19	96.08	97.32
MIT-BIH Arrhythmia DB	97.07	96.95	98.22

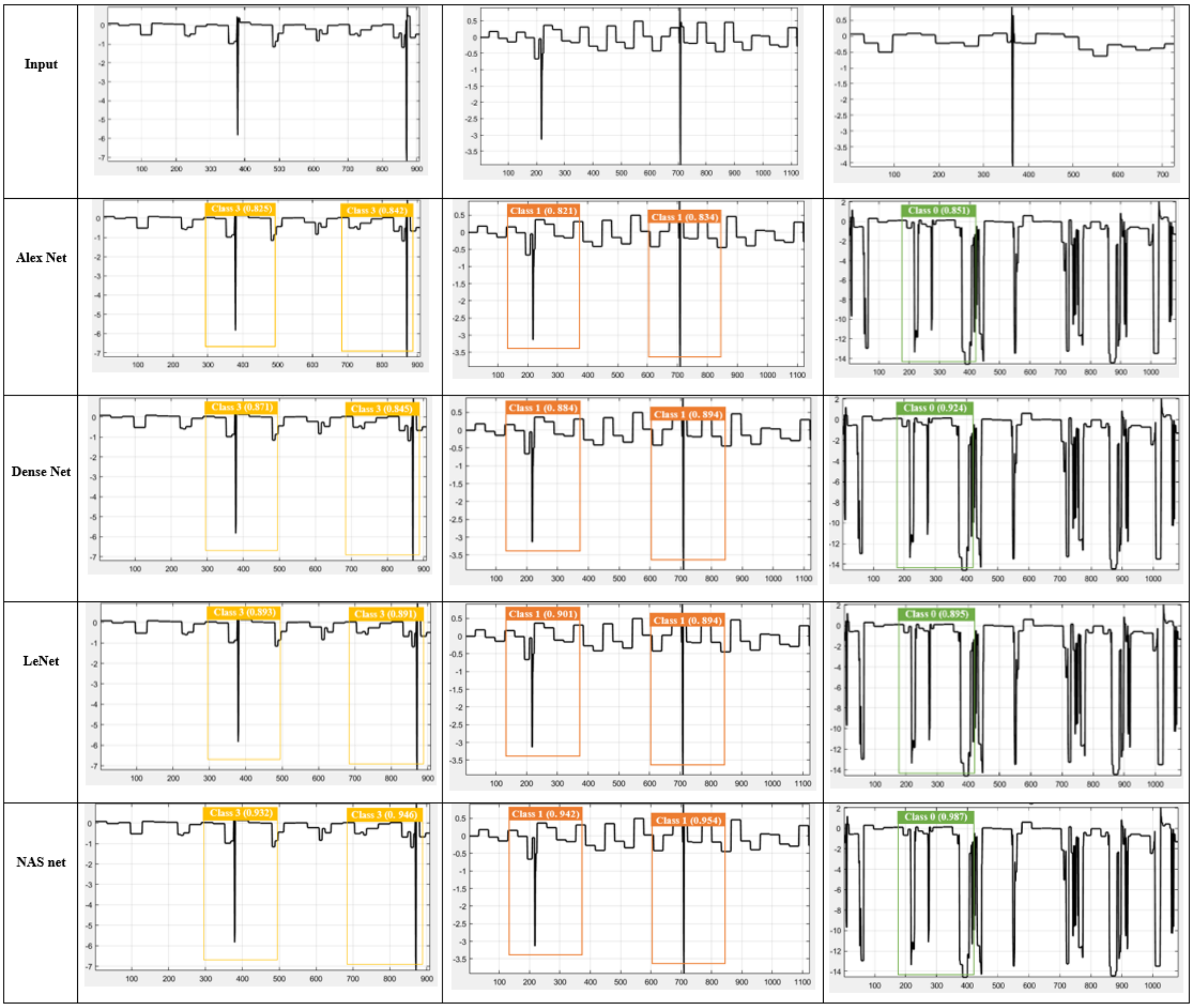


Fig. 8. Comparison of different detection networks for ECG signals.

Fig.8 displays a comparison of the proposed NASNet with the various conventional DL networks such as AlexNet, DenseNet, and LeNet respectively for the Arrhythmia classification based on ECG signals. An example of an ECG input signal is shown in line 1, while the results of multiple detection methods are shown in the following lines. This comparison shows that AlexNet performs less accurately than the other networks in terms of classification accuracy. Furthermore, DenseNet and LeNet achieve almost identical results in ECG classification. However, these detection networks did not match the performance of NASNet in identifying ECG arrhythmias.

D. Clinical integration

In sensitive areas such as healthcare, deep learning algorithms represent a significant obstacle to adoption. This makes it difficult for anyone to understand them and to come to a specific conclusion. The complexity of intricate models such as deep neural networks makes them harder to understand. It is more difficult to determine which important features of ECG signals have the greatest influence on the predictions made by intricate models. By learning the underlying features of the algorithms, clinicians can ask pertinent questions about the model's predictions.

The clinical integration of the proposed SID-NASNet is shown in Fig. 9. During training, the network aimed to reduce the discrepancy between the projected and actual outcomes by determining the ideal weights and biases. The weight value in the network was updated according to the age of the patients to provide an accurate prediction. This technique utilizes the ECG signal features that complement clinical workflows and make them more accessible to real-world healthcare.

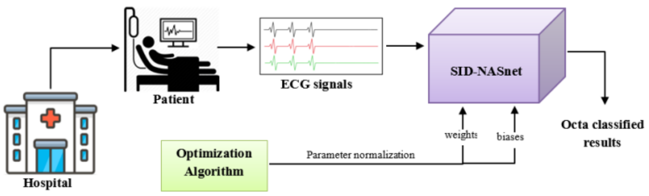


Fig. 9. Clinical integration of the proposed model.

5. CONCLUSION

This research introduces a novel SID-NASNet for the classification of ECG arrhythmia abnormalities using wearable monitoring devices. ECG signals were first acquired in real-time using 12-lead electrodes and denoised using DWT to remove repetitions and improve robustness. These denoised signals were then fed into the NASNet network, which was enhanced with Stripped convolutional layers to detect arrhythmia abnormalities. The SID-NASNet uses the DO algorithm to normalize the parameters, which reduces network complexity and improves model competence. The classification results show that the integration of ECG data from the MIT-BIH dataset improves the performance of the SID-NASNet model. According to the results of the conducted experiments, the proposed model adeptly distinguishes arrhythmia ECG signals and achieves an impressive overall accuracy of 99.24%. The proposed NASNet achieves 4.11%, 3.12%, and 2.20% better overall accuracy than AlexNet, DenseNet, and LeNet, respectively. Moreover, the proposed SID-NASNet improves the accuracy by 0.22%, 2.76%, and 0.85% better than ECG-NET, DL-based GAN, and 1D-CNN, respectively. The proposed SID-NASNet is extremely reliable and utilizes advanced GPUs to efficiently process large amounts of ECG data and classify arrhythmias in real time. It enables fast monitoring of cardiac activity. The future implementation includes an FPGA setup for efficient heartbeat abnormality detection.

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