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Deep Residual Networks with Synthetic Minority Over-Sampling Technique Edited Nearest Neighbours (SMOTE-ENN) for ECG Monitoring for Arrhythmia Classification

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ABSTRACT

The electrocardiogram (ECG) is one of the most important physiological markers utilised in arrhythmia diagnosis. The ECG arrhythmia classification devices, which include multi-module sensors, clustering algorithms and neural networks, have established themselves as vital monitoring and detection systems for cardiovascular disorders during the last few years. The current ECG arrhythmia classification algorithms encounter two main difficulties because they have complicated models and they need extended periods to complete their operations. The identification of arrhythmias in ECG data needs precise evaluation to perform successful cardiac monitoring and receive correct medical care. The main problem with ECG dataset analysis through deep learning methods stems from the unbalanced distribution of arrhythmia types, which makes some arrhythmia types less common than others. This research presents a new method to enhance arrhythmia detection from ECG data by integrating deep residual networks (ResNets) with the synthetic minority over-sampling technique - edited nearest neighbours (SMOTE-ENN). The ResNet architecture serves to extract deep hierarchical features from ECG data, which enables the model to learn complex arrhythmia patterns with high accuracy. The system uses SMOTE-ENN to create artificial minority class examples while it eliminates unimportant and borderline data points, which produces a dataset that is both clean and balanced. The proposed framework demonstrates superior performance to conventional methods according to experimental results, which were conducted on ECG benchmark datasets. The combination of ResNet with SMOTE-ENN produces better model generalisation, which results in improved accuracy, F1-score, and sensitivity performance, especially for the minority arrhythmia classes. The research shows that deep learning systems, which use improved data balancing techniques,

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can successfully detect arrhythmias in ECG monitoring systems which function in actual clinical settings.

Keywords: Arrhythmia classification, deep learning, deep residual networks (ResNets), electrocardiogram (ECG), synthetic minority over-sampling technique-edited nearest neighbours (SMOTE-ENN)

INTRODUCTION

The public health situation has become more critical because arrhythmias and other cardiovascular diseases now represent major health risks (Hong et al., 2022). While ventricular tachycardia and ventricular fibrillation (Sangha et al.,2022) necessitate prompt medical attention, atrial premature beats are examples of arrhythmias that require regular monitoring or surveillance. The unpredictable pattern of arrhythmia events, which last only briefly, makes it challenging to detect these events through 24-hour ambulatory ECG monitoring or standard ECG recordings. The system provides vulnerable people with current cardiac information and correct medical guidance through real-time ECG monitoring, which runs on wearable or portable devices to reduce medical facility workload and decrease their chances of getting sick (Liu et al.,2022).

The 12-lead ECG serves as a clinical image processing tool which cardiologists use to detect cardiovascular diseases while performing precise cardiac health evaluations of their patients. The research by Al-Zaiti et al. (2025) investigates medical diagnosis through their study and prediction using pre-hospital 12-lead ECGs, which have been the focus of prior studies. Several challenges persist in achieving successful non-clinical self-monitoring ECG detection. Nonmalignant arrhythmias, which include atrial premature beats and nonpersistent sinus tachycardia, ventricular premature beats and sinus bradycardia, show small variations from their typical ECG readings because of various clinical and physiological factors. The evaluation of these minimal differences requires either specialised equipment or medical professionals with advanced training for accurate assessment. The new technology enables customers to monitor their heart rate precisely through wearable devices, which alert them about abnormal heart rhythms that include atrial fibrillation and premature beats. Modern monitoring systems use robust programs, which Liu et al. (2024) describe in their research. The system lets users check their heart health status while they monitor their medications and complete various health tasks. To improve the precision and effectiveness of organisational outcomes, further study is needed into the integration of lightweight neural networks with ECG monitoring methods (Liu et al.,2022; Qaisar et al.,2022).

The system for ECG-based arrhythmia classification becomes effective through the combination of deep residual networks (ResNets) with the synthetic minority over-sampling technique and edited nearest neighbours (SMOTE-ENN). The ResNet network solves vanishing gradient problems while extracting hierarchical features, but SMOTE-ENN addresses class imbalance, which occurs frequently in ECG datasets. The SMOTE algorithm produces artificial examples which improve minority class representation, while Enn eliminates unnecessary data points to develop an improved dataset that produces superior model performance. The hybrid method enables doctors to identify arrhythmias with high precision, which leads to better real-time cardiac monitoring and diagnosis results.

Research of Our Work

The research investigates a deep residual network architecture, which incorporates SMOTE-ENN for ECG monitoring and arrhythmia organisation to determine how combining state-of-the-art deep learning techniques with data preprocessing methods will enhance arrhythmia detection accuracy. The research uses deep residual networks to extract and analyse complex patterns in ECG signals, combined with SMOTE-ENN to address class imbalance by synthesising minority class samples and eliminating noisy data. The method enhances both precision and system stability for cardiovascular health tracking, which enables doctors to detect arrhythmias at early stages before they develop into severe conditions, thus resulting in improved patient outcomes.

Motivation of this Research

Scientists need to develop reliable arrhythmia detection systems which identify dangerous heart rhythm problems for this research purpose. The process of monitoring electrocardiograms (ECGs) enables doctors to make early diagnoses, but ML models struggle because their training data contains unbalanced information, which makes aberrant instances occur rarely. The research combines deep residual networks (ResNets) with SMOTE-ENN to solve data imbalances, which results in better classification results. The main objective of this research is to improve diagnostic accuracy through the combination of SMOTE-ENN preprocessing strength with ResNet's feature extraction capabilities. The system will lead to better medical results for patients while it develops new automated healthcare systems.

The Main Contributions of this Work

- To develop a unique strategy for enhancing arrhythmia detection from ECG data by merging deep residual networks (ResNets) with SMOTE-ENN
- To address class imbalance, SMOTE-ENN is employed to generate synthetic minority class samples while eliminating noisy and borderline data points, resulting in a cleaner and more balanced dataset.

- Finally, experimental outcomes on benchmark ECG datasets demonstrate that the suggested framework outperforms traditional approaches.

Structure of Our Article

The rest of the article is structured as follows: Section 2 provides a thorough literature assessment, while Section 3 outlines the proposed technique. The research results and analysis appear in Section 4, followed by a conclusion that presents the study's findings and suggests additional research directions.

Literature Survey

The research investigates new ECG monitoring systems which identify arrhythmias through an analysis of current diagnostic approaches and classification methods, and their application in healthcare settings. The identification of cardiovascular health issues at their earliest stages requires ECG-based monitoring systems that can detect arrhythmias with high precision and speed. The study investigates present-day arrhythmia detection methods which use machine learning (ML) and deep learning (DL), and wearable device technology, while it determines their present-day obstacles and their prospective uses.

Zheng et al. (2020) created an arrhythmia recognition system which used CNNs and LSTM to identify eight ECG data categories, including normal sinus rhythm. The article used ECG data from the MIT-BIH arrhythmia database. The model received its input data through the conversion of one-dimensional signals, which became two-dimensional greyscale images. To detect and categorise the incoming data, the combination model was used. The benefit of this technique is that the ECG signal does not need to be feature-extracted or noise-filtered.

A new feature extraction technique was proposed by Zou et al. (2022) for better heartbeat categorisation. Segment label features were learned by a convolutional neural network and then fed into a random forest classifier with other standard features. Using the MIT-BIH arrhythmia database, the model was trained to classify three different heartbeat types: NEB, VEB, and SVEB. The method obtained a 96% accuracy rate and an F1 score of 88.3% for each of these classes. The research established that segment labels play a vital role in accurate heart rhythm classification because they provide essential contextual information.

Ganguly et al. (2020) created a DL system which employed LSTM methods to perform automatic arrhythmia detection and ECG recording extraction. A feature-based bidirectional LSTM (bi-LSTM) system took the role of the conventional LSTM network architecture. The analysis used bidirectional multifractal detrended fluctuation analysis to extract relevant features. Multifractal parameters were utilised to analyse the complex, stochastic, and nonlinear fluctuations of the online-accessible ECG data. A single-layer bi-LSTM method was fed ten characteristics extracted from the segmented ECG beats.

The research by Atal and Singh (2020) developed a deep convolutional neural network (deep CNN) which uses optimisation to perform automatic arrhythmia organisation. They presented the Bat-Rider Optimisation Algorithm (BaROA), a new optimisation method that combines the Rider Optimisation Algorithm (ROA) and the Multi-Objective Bat Algorithm (MOBA). Wavelet and Gabor features were recovered in the first step since the signals represented different ECG components. These features were then processed by a BaROA-based DCNN classifier to differentiate between arrhythmia and non-arrhythmia cases. The techniques were evaluated utilising the MIT-BIH arrhythmia database. The corresponding outcomes were 93.19%, 95%, and 93.98% for accuracy, specificity, and sensitivity, respectively.

Fatimah et al. (2024) proposed an inter-patient paradigm to address the challenges of generalisation, where the test dataset was collected from a participant group rather than the training dataset. Their suggested method achieved an F1 score of 89.35% in detecting supraventricular ectopic beats (SVEB) compared to existing methods. They analysed ECG data on multiple scales using the Fourier decomposition method (FDM). The narrow-band signal elements produced by FDM were used to extract time-domain and statistical features. To eliminate redundancy and rank the most significant attributes, two feature selection methods, the Kruskal-Wallis test and minimum redundancy maximum relevance (MRMR), were employed.

Katal et al. (2023) investigated the accuracy, specificity, precision, and F1 score of their DL-based techniques for identifying arrhythmias from ECG signals. To evaluate its performance against pretrained models such as GoogLeNet, they propose building a compact CNN. The comparative analysis highlights the promising potential of diagnosing arrhythmias using ECG signals and deep learning.

Kumar et al. (2022) proposed an optimized dl classifier for the automatic identification and categorisation of arrhythmias. First, ECG data collected by IoT nodes is used to extract the QRS complex and the RR interval. These are then utilised to create the feature vector for arrhythmia organisation. The ECG signal anomalies are found using a deep convolutional neural network based on coy-grey wolf optimisation (coy-gwo-based deep CNN) classifier. To efficiently update the classifier's parameters, the suggested coy-gwo technique makes use of hybrid data, such as social hunting hierarchies and canid hunting experiences.

Varshney et al. (2022) and their co-authors developed a method to analyse ECG data through software which organises heart rhythm information by arrhythmia type. The researchers applied an undecimated discrete wavelet transform (UDWT) to break down each signal. The system performed ECG waveform reconstruction to detect R-peaks through its application of specific frequency bands. To categorise various arrhythmia forms, the heart rate was determined. The capacity of the UDWT-based method to dissect signals at numerous levels makes it beneficial for a variety of processing applications. In the frequency and time domains, it also makes simultaneous localisation easier.

Research Gap

The research field of ECG monitoring for arrhythmia classification has achieved significant advancements, but it still encounters various unresolved difficulties (Mekruksavanich & Jitpattanakul, 2024). The current systems depend on human-made features and particular datasets, which restrict their ability to work with different patient groups in actual clinical settings. The current methods fail to identify both infrequent and concurrent arrhythmia types, which leads to lower detection precision. The lack of effective real-time monitoring systems which work with wearable devices prevents most medical facilities from adopting these technologies. Researchers need to develop complex ML models which will automatically identify important features to solve these existing problems.

Problem Identification in the Existing System

Many systems face challenges in accurately classifying arrhythmias in real time due to noise, artefacts, and variability in ECG signals across patients.

- Most models are trained on datasets that fail to fully represent diverse patient populations, resulting in biases and reduced performance in real-world applications.
- Current systems often depend on complex hardware and expensive computational resources, limiting accessibility, particularly in low-resource settings.
- Wearable or moveable devices encounter issues with battery life, restricting long-term monitoring and continuous data collection.

Our Proposed Model

The research presents an original method to enhance ECG-based arrhythmia detection through the integration of deep residual networks (ResNets) with SMOTE-ENN. ResNets are employed to extract deep hierarchical features from ECG data, enabling accurate learning of complex patterns connected with various arrhythmias. The system uses SMOTE-ENN to create artificial minority class examples while removing unimportant and uncertain data points, which produces a dataset that is both clean and balanced. This work introduces a hybrid framework for ECG-based arrhythmia classification that combines residual deep learning architectures with a data-level imbalance correction strategy using SMOTE-ENN.

The block diagram for the suggested model is shown in Figure 1. This architectural design displays a pipeline for categorising arrhythmias utilising the MIT-BIH arrhythmia database. The system starts with data preprocessing, which uses a six-layer wavelet transform to clean ECG signals and produce ECG images. Ngo et al. (2022) the process of heartbeat segmentation enables researchers to extract individual cardiac cycles from the recorded data. The system uses deep residual networks (ResNets) to extract features through their convolutional layers, which include residual connections for achieving both high accuracy and efficient feature extraction. Finally, the SMOTE-ENN method is employed

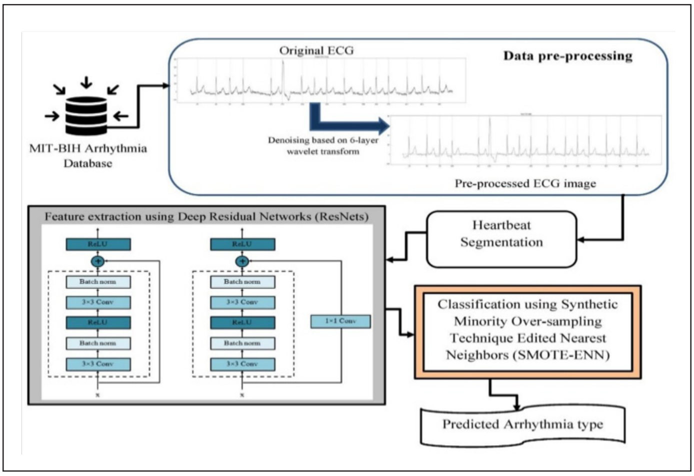

Figure 1. Block diagram for the proposed model

for classification to address class imbalance in the dataset and predict arrhythmia types. The method generates powerful feature extraction results while it effectively manages unbalanced data, which produces superior classification results.

Dataset

The experiments were conducted using the MIT-BIH arrhythmia database, a widely accepted benchmark for evaluating arrhythmia detection methods. The database consists of annotated ambulatory ECG recordings obtained from multiple subjects under controlled conditions shows in Figures 2 and 3. For consistency across experiments, only the modified lead II signal was utilised in this study. Heartbeat annotations were grouped into five standard classes in accordance with AAMI recommendations: normal (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion beat (F), and unclassifiable beat (Q) show in Table 1. Due to the dominance of normal beats, the dataset exhibits significant class imbalance, motivating the use of advanced resampling strategies.

Table 1
Testing and training are divided for every class

Class	Meaning	Training samples	Samples	Proportion (%)	Test samples
S	Supraventricular premature or Ectopic beat	2223	2779	2.54	556
N	Normal beat	72,471	90,589	82.77	18,118
V	Premature ventricular contraction	5788	7236	6.61	1448
F	Fusion of ventricular and normal beat	641	803	0.73	162
Q	Unclassifiable beat	6431	8039	7.35	1608
Total		**87,554**	**109,446**	**100.00**	21,892

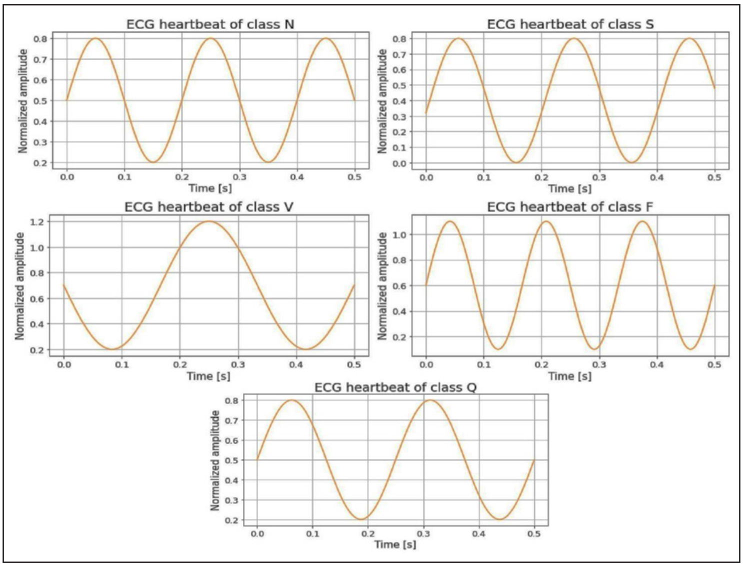

Figure 2. Samples of random ECG heartbeats

Data Preprocessing

Before feature extraction, ECG signals were processed using a multi-level wavelet-based denoising approach (Qin et al.,2024). This step reduces baseline drift and high-frequency interference while preserving clinically relevant waveform characteristics. R-peak detection was then performed to segment the ECG signals into individual cardiac cycles.

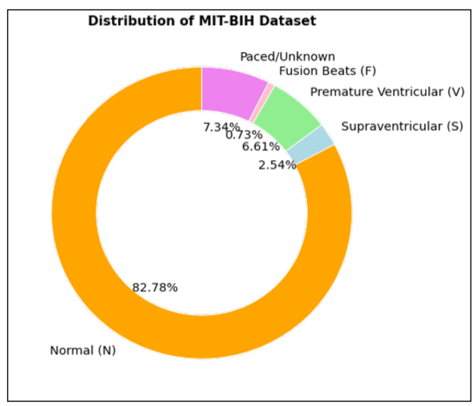

Figure 3. Distribution of the dataset

Each extracted heartbeat was normalised and transformed into a standardised input format suitable for deep learning. These steps ensure uniform representation across samples and improve the stability of the training process in Equation 1 and Equation 2.

$$cA_{i+1}(y) = \sum_x cA_j\,(x)h(x-2y) \qquad [1]$$

$$cD_{j+1}(y) = \sum_x cA_j\,(x)\,g(x-2y) \qquad [2]$$

The following is the reconstruction equation defined in Equation 3:

$$A_j\,(y) = \sum_x cA_{j+1}(x)h\,(y-2x) + cD_{j+1}(x)g(y-2x) \qquad [3]$$

The analysis of ECG data requires the identification of essential waveforms, which doctors need to diagnose cardiac diseases. The process required the following sequence of operations.

1. The positive and negative peak values of the ECG signal were identified.
2. The maximum values from the calculation allowed us to determine the peak and valley points of the ECG waveform. The signal waveform shows heart voltage changes during a cardiac cycle, but its peak values represent the maximum and minimum points. The most noticeable aspects of the ECG indication, the R-waves of the QRS complex, which typically correspond to peaks, are indicative of ventricular polarisation.
3. The T-waves, which are an element of the repolarisation process and come after the P-waves, can be regarded as troughs.
4. The research team removed excess r-waves which appeared by accident while they added any absent R-waves to preserve the complete ECG signal.
5. The QRS complex, T-wave, and P-wave were detected through the current threshold settings.

Healthcare providers use systematic methods to diagnose ECG waveforms, which enable them to detect cardiac conditions. Based on the R waves, the test results were classified into several cycles: 200 R, 200 A, 300 V, 400 N, and 300 L in total. Ten ECG signals from each classification, totalling 50, were selected as the fitting dataset. There were 250 ECG signals, 50 from each group, in the training dataset. 466 ECG signals, in total: 80 A, 110 N, 110 L, 110 R, and 56 V, were selected for study. To prevent falsely high classification accuracy, there was no overlap between the fitting, training, and testing datasets.

Deep Residual Networks (ResNets)

Deep residual networks form the backbone of the proposed feature extraction process. Unlike traditional deep neural networks, residual architectures incorporate shortcut connections that allow information to bypass certain layers (Fan et al., 2020). This design facilitates efficient gradient propagation and enables the training of deeper models without performance degradation. The network is composed of multiple residual blocks, each containing convolutional layers followed by normalisation and activation functions shows in Figure 4. By learning residual mappings, the model effectively captures temporal and morphological patterns associated with different arrhythmia types.

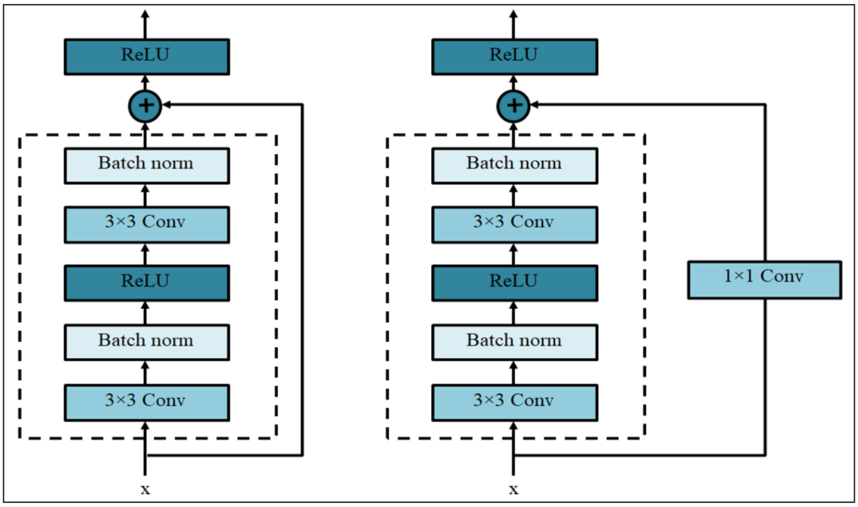

Figure 4. The architecture of the ResNet model

Residual Learning Framework

ResNets explicitly reformulate the layers to learn residual functions $F(x) = H(x) - x$ instead of directly learning $H(x)$, where $H(x)$ is the desired mapping, and x is the input. The residual function is easier to optimise because it assumes the identity mapping $H(x) = x$ as an initial approximation. Thus, the output of the block becomes, according to Equation 4:

$$y = F(x) + x \quad [4]$$

Identity Shortcut Connections

These are direct pathways that bypass one or more layers in the network. For example, in a block with two convolutional layers, the input x skips these layers and is added to the output of the second layer. Mathematically, defined in Equation 5:

$$y = \sigma(F(x, \{W_k\}) + x \quad [5]$$

wherever W_k are the learnable parameters of the convolutional layers and σ is the activation function of ReLU.

Block Structure

Resnets are composed of multiple residual blocks, which typically include:

- a convolutional layer
- batch normalisation

- non-linear activation (ReLU)
- an identity shortcut connection

For example, a simple block can be represented by Equation 6:

$$y = ReLU\left(BN\left(W_2.ReLU\left(BN(W_1.x)\right)\right) + x\right) \quad [6]$$

where W_1 and W_2 are weight matrices for two convolutions, and bn represents batch normalisation.

Depth and Performance

The key advantage of ResNets lies in their ability to train extremely deep networks without experiencing a degradation in performance. For example, a 152-layer ResNet outperformed shallower models on the ImageNet dataset.

Gradient Flow

In standard deep neural networks, gradients tend to diminish as they backpropagate, leading to poor learning in the earlier layers. In ResNets, the gradient of the loss function L with respect to parameters W in a residual block container can be expressed as Equation 7:

$$\frac{\partial L}{\partial W} = \frac{\partial L}{\partial y}.\left(\frac{\partial F(x)}{\partial W} + \frac{\partial x}{\partial W}\right) \quad [7]$$

The second term ensures that gradients can propagate effectively even if $F(x)$ is close to zero.

Training Objective

The loss L is minimised by optimising both the residual function $F(x)$ and the identity mapping. For a network with nnn layers, the output at layer k can be recursively expressed as Equation 8:

$$x_k = x_{k-1} + F(x_{k-1}, W_k) \quad [8]$$

Variants and Improvements

Bottleneck Residual Blocks

To reduce computational cost in very deep networks, bottleneck structures are used, where the block consists of 1 × 1, 3 × 3, and 1 × 1 convolutions according to Equation 9:

$$y = W_3 . ReLU\big(W_2 ReLU(W_1 . x)\big) \quad [9]$$

ResNet with Pre-Activation

An improved variant includes batch normalisation and ReLU applied before convolutions, which enhances optimisation.

Synthetic Minority Over-Sampling Technique Edited Nearest Neighbours (SMOTE-ENN)

SMOTE

SMOTE is a resampling method that creates synthetic samples in the feature space of the minority class to rectify class imbalance. This is accomplished using linear interpolation between the minority class's current samples and their k-nearest neighbours (Hai Ly et al., 2022).

Mathematically, given a sample x_i since the minority class and one of its k-nearest neighbours x_k, a synthetic sample x_{new} is generated in Equation 10:

$$x_{new} = x_i + \lambda(x_k - x_i) \quad [10]$$

wherever λ Is a random number drawn from a uniform distribution. $\lambda \sim U(0,1)$. This ensures the synthetic sample lies along the line segment connecting x_i and x_k, introducing diversity in the feature space while maintaining realistic boundaries for the minority class.

Edited Nearest Neighbours (ENN)

ENN is a data cleaning method applied after oversampling to remove potential noise and borderline cases. It operates by examining the k-nearest neighbours of each sample and removing samples whose class labels differ from the majority of their neighbours' labels.

Given a sample x_i, let $N_k(x_i)$ represent its k-nearest neighbours. The decision for retention is based on the agreement of x_i's label yi with the majority label $y_{majority}$ in $N_k(x_i)$ according to Equation 11:

$$y_{majority} = mode\big(\{y_j \,|x_j \in N_k(x_i)\}\big) \quad [11]$$

if $y_i \neq y_{majority}$, the sample x_i is removed from the dataset. This process cleanses noisy data and enhances the decision boundaries, especially for imbalanced datasets.

SMOTE-ENN

SMOTE-ENN links the advantages of ENN and SMOTE. The ENN system removes both incorrect and noisy data points which exist in both synthetic and original data sets. The SMOTE system generates artificial data points to achieve class distribution equilibrium.

Let the combined dataset after SMOTE be D_SMOTE as defined in Equation 12, and the processed dataset after ENN be D_(SMOTE-ENN) as defined in Equation 13. Formally:

1. Apply SMOTE to obtain:

$$D_{SMOTE} = D_{original} \cup D_{synt\,hetic} \quad [12]$$

where $D_{synt\,hetic}$ includes newly generated samples.

2. Use ENN for data cleaning:

$$D_{SMOTE-ENN} = \{x_i \in D_{SMOTE} | y_i = mode(\{y_j | x_j \in N_k(x_i)\})\} \quad [13]$$

This two-step process improves class balance and enhances decision boundary clarity, leading to better classifier performance, particularly on imbalanced datasets.

Advantages of the Proposed Method

- SMOTE-ENN ensures better representation of the minority class, a critical component in the grouping of arrhythmias, by resolving the problem of imbalanced distribution of ECG datasets.
- A combination of deep residual networks (ResNets) with SMOTE-ENN allows deep learning models to discover intricate patterns from balanced data, which produces superior prediction accuracy.
- The ENN component eliminates unnecessary data points, which produces better training data quality and makes the model more stable.

RESULT AND DISCUSSION

Implementation Details

PyTorch and Python were used to implement the framework. The training process for all neural networks occurred on a laptop which contained an Intel i7-7820HK CPU and an NVIDIA GeForce GTX 1080 GPU. The confusion matrix from the dataset appears in Figure 5.

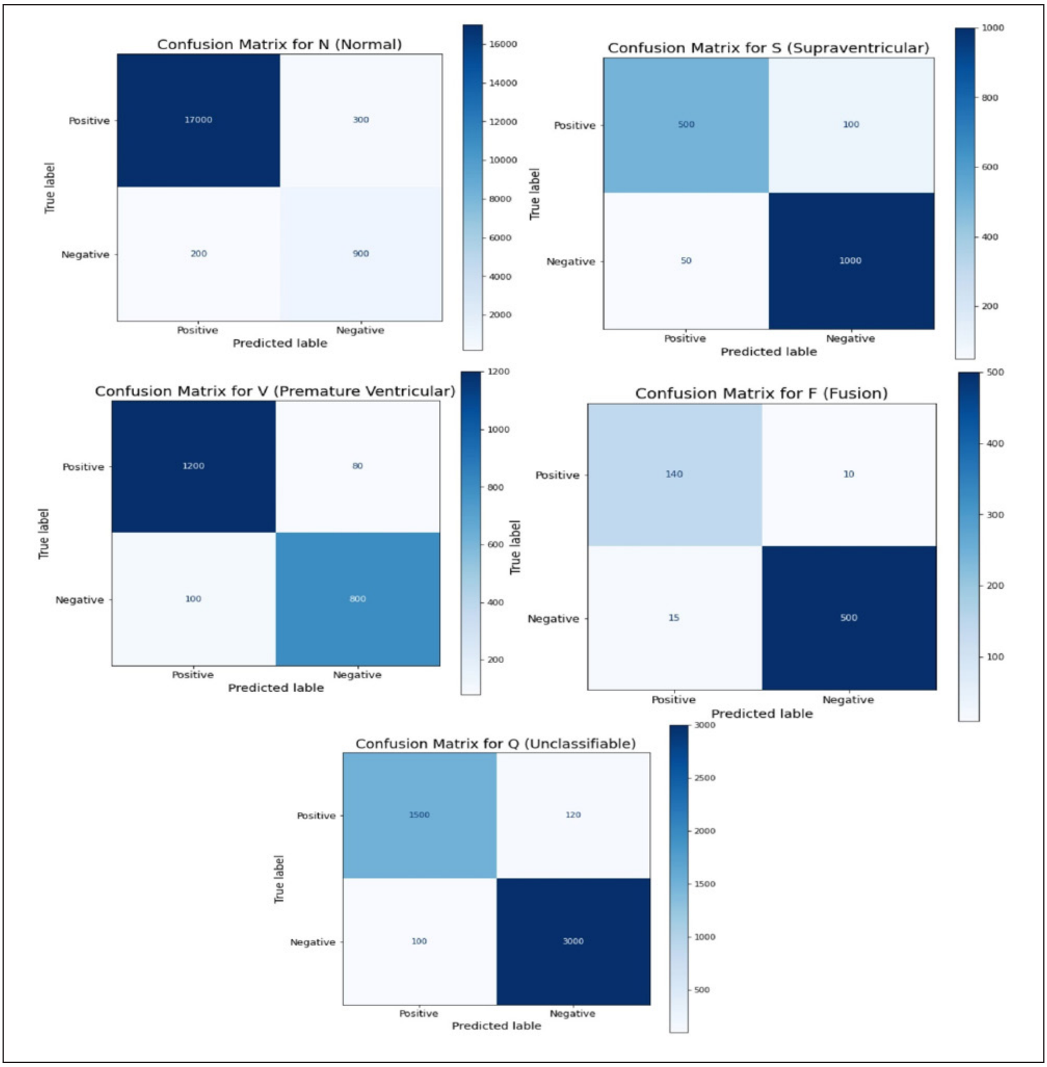

Figure 5. Confusion matrices for each ECG beat class (n, s, v, f and q)

Performance Metrics

Organisations achieve accurate organisational models through their use of precise measurement systems, which enable them to assess their operational performance. The system calculates the percentage of correctly predicted positive events from all the positive events that were projected. The level of precision in a system determines how many incorrect results it produces according to Equation 14.

$$\Pr ecision = \frac{TP}{TP + FP} \quad [14]$$

The classification process requires recall to identify the correct proportion of true positive examples which the system correctly identifies according to Equation 15. The true positive rate (TPR) and sensitivity are other names for it.

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \quad [15]$$

A classification model achieves its accuracy through the ratio of correct predictions to all its generated forecasts, which serves as its main performance evaluation metric according to Equation 16.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad [16]$$

The performance of binary classification systems is assessed using a statistic called the Matthews correlation coefficient (MCC). The system provides a fair assessment through its evaluation of false negatives, true positives, true negatives and false positives according to Equation 17. The method delivers its best results when working with datasets which contain unbalanced data points.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad [17]$$

An indicator of the discrepancies between expected and observed values is the root mean square error (RMSE). The method generates a single value which represents the square root of the average squared changes to determine forecast precision according to Equation 18.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \quad [18]$$

The accuracy of a predictive model can be evaluated using a metric called MAPE (mean absolute percentage error). The mean of the absolute proportion errors between the expected and actual values is calculated according to Equation 19.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right| \times 100 \quad [19]$$

The duration which a program or algorithm needs to finish its execution cycle determines its running time. It is often expressed as a function of the input size n and varies depending on the algorithm's complexity as expressed by Equation 20.

$$T(n) = O(f(n)) \quad [20]$$

Comparative Methods

FRM-CNN (Fusing Rhythmic Morphological-Convolutional Neural Network)

Fan et al. (2020) FRM-CNN outperforms state-of-the-art recognition approaches in tracking people's health problems using mobile devices.

MRFO-SVM (Manta Ray Foraging Optimisation-Support Vector Machine)

Houssein et al. (2021) note that while MRFO is used to optimise the limits of SVM and select the subset of pertinent characteristics that guarantees the optimal organisation presentation, SVM is utilised for organisation in the MRFO-SVM technique.

AE-biLSTM (Auto- Encoder and Bidirectional Long Short-Term Memory)

Ramkumar et al. (2022) proposed the AE-biLSTM technique, which consists of a decoder that utilises a biLSTM network to reconstruct the electrocardiogram arrhythmia signals, and an encoder that employs a biLSTM network to extract higher-level features from the signals.

Table 2 and Figure 6 present the comparative analysis of the models FRM-CNN, MRFO-SVM, AE-biLSTM, and the proposed model across Precision, Recall, Accuracy,

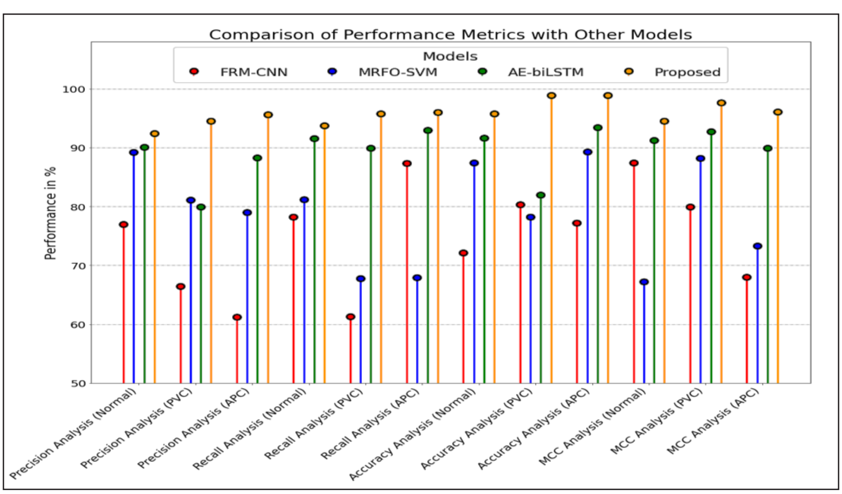

Figure 6. Comparison of performance metrics with other models

Table 2
Comparison of performance metrics with other models

Models	Precision Analysis			Recall Analysis			Accuracy Analysis			MCC Analysis		
	Normal	PVC	APC	Normal	PVC	APC	Normal	PVC	APC	Normal	PVC	APC
FRM-CNN	76.98	66.44	61.22	78.22	61.33	87.33	72.11	80.33	77.21	87.44	79.91	67.98
MRFO-SVM	89.22	81.11	78.98	81.22	67.76	67.91	87.44	78.22	89.33	67.22	88.22	73.33
AE-biLSTM	90.11	79.91	88.31	91.55	89.91	92.99	91.66	81.98	93.45	91.22	92.76	89.91
Proposed	92.43	94.55	95.66	93.76	95.76	95.98	95.76	98.87	98.90	94.55	97.65	96.11

and MCC metrics, revealing notable differences in performance. The FRM-CNN model exhibited lower performance, particularly in Precision and MCC, with values of 66.44 for Premature Ventricular Contraction (PVC) and 61.22 for Atrial Premature Contraction (APC), and an MCC score of 67.98 for APC. The MRFO-SVM model achieved better results than FRM-CNN because it produced 89.22 Normal Precision and 89.33 APC Accuracy scores. However, it still lagged the other models in Recall and MCC. The AE-biLSTM model achieved excellent results in all evaluation criteria by reaching 90.11 Precision for Normal data and 88.31 Precision for APC data while maintaining high Accuracy and Recall performance, but did not match the performance of the recommended model. The suggested model performed better than all other models in every evaluation metric by achieving the highest Precision (95.66 for APC), Recall (95.98 for APC), Accuracy (98.90 for APC) and MCC (96.11 for APC). The proposed model demonstrates better performance than other models because it achieves the best combination of Precision and Recall and classification Accuracy.

Table 3 and Figure 7 demonstrate that the models were evaluated through RMSE and MAPE metrics, which measured their ability to make accurate predictions. The FRM-CNN model produced high RMSE results, which reached 34.56 for PVC and 24.76 for APC, while the MAPE values reached 22.11 for PVC and 25.98 for APC. The MRFO-SVM model achieved average results, but its RMSE values reached 31.11 for Normal and 29.98 for PVC, and its MAPE values reached 39.11 for PVC and 35.87 for APC. The AE-biLSTM model produced results that were evenly distributed because its RMSE values spanned from 29.98 to 33.87 and its MAPE values spanned from 26.76 to 30.22. The proposed model achieved the best results in RMSE and MAPE performance because it produced the lowest RMSE values of 10.67 for Normal and 12.11 for APC, and MAPE values of 15.77 for PVC and 19.54 for APC.

Table 3
Comparison of RMSE and MAPE analysis

Models	RMSE Analysis			MAPE Analysis		
	Normal	PVC	APC	Normal	PVC	APC
FRM-CNN	23.87	34.56	24.76	32.87	22.11	25.98
MRFO-SVM	31.11	29.98	29.11	29.11	39.11	35.87
AE-biLSTM	29.98	30.33	33.87	30.43	26.76	30.22
Proposed	10.67	14.22	12.11	18.22	15.77	19.54

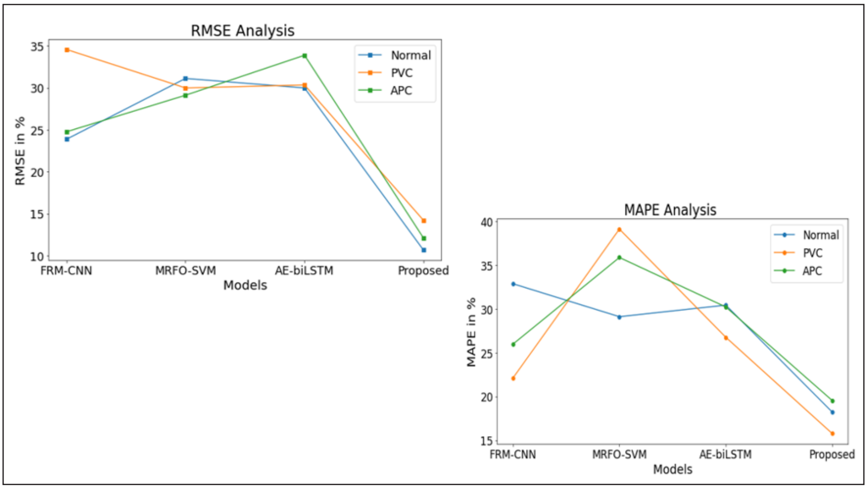

Figure 7. Comparison of RMSE and MAPE analysis

The running time analysis of the models appears in Table 4 and Figure 8, which demonstrates substantial variations between the models. The FRM-CNN model produced the longest running times, which reached 10.654 seconds for Normal, 12.843 seconds for PVC and 14.765 seconds for APC. The MRFO-SVM model showed slightly lower running times for PVC at 6.765 but generally higher values for Normal and APC. The AE-biLSTM model showed typical execution times because Normal produced the longest time of 14.876 seconds, while PVC and APC produced shorter times. The proposed model delivered the fastest results in every

Table 4
Running time evaluation

Models	Running Time Analysis		
	Normal	PVC	APC
FRM-CNN	10.654	12.843	14.765
MRFO-SVM	13.562	6.765	12.765
AE-biLSTM	14.876	8.543	8.113
Proposed	1.654	3.765	5.564

test scenario because it produced the shortest execution times, which reached 1.654 seconds for Normal, 3.765 seconds for PVC and 5.564 seconds for APC.

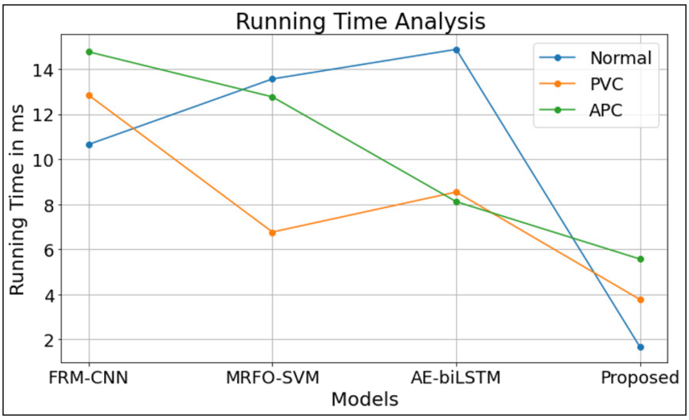

Figure 8. Running time analysis of the proposed model

DISCUSSION

The comparison of various models across multiple presentation metrics highlights the superior presentation of our model. The research by Fan et al. (2020) produced results that were lower than ours for Precision, Recall, Accuracy, MCC, RMSE and MAPE. Our model achieved superior results to all other models in the study. The precision of our model was 95.66 for APC, which surpassed 61.22 for APC. The model achieved significant enhancements in Recall and Accuracy, and MCC performance, which reached 95.98, 98.90 and 96.11 for APC, respectively. The model achieved high prediction accuracy through its RMSE scores of 10.67 for Normal and MAPE scores of 15.77 for PVC. The model achieved the best performance regarding running time because it demonstrated the lowest execution times of 1.654 for Normal and 5.564 for APC among all tested models. The complete evaluation demonstrates that our model achieves superior results to other models because it achieves both high precision and fast computation speed.

Ablation Study Analysis

Table 5 and Figure 9 show the accuracy of three different methods used for performance evaluation. The ResNet model achieved an accuracy of 92.76%, while the SMOTE method, which addresses class imbalance, improved the accuracy to 95.56%. The combination of ResNet with SMOTE-ENN produced better results, achieving an accuracy of 97.84%. The results indicate that SMOTE

Table 5
Ablation study analysis

Method	Accuracy
ResNet	92.76
SMOTE	95.56
ResNet + SMOTE-ENN	97.84

integration with ResNet produces better results when SMOTE-ENN is used for improved data balancing.

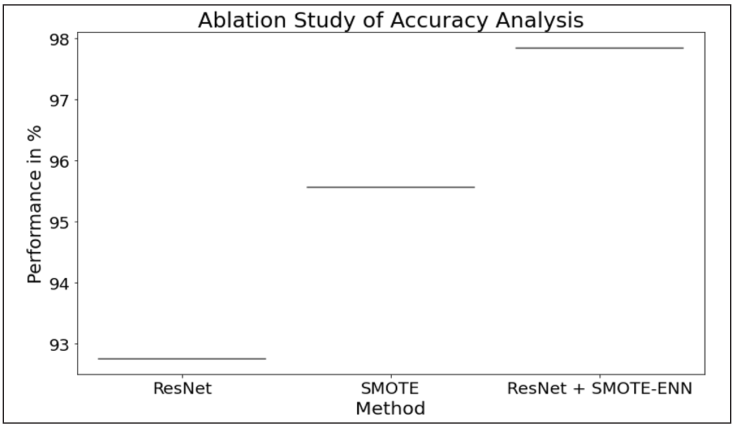

Figure 9. Ablation study and performance analysis

Training Validation Loss and Accuracy Analysis

The system operates by training itself while it tracks both validation loss and accuracy values. Figure 10 illustrates that ECG monitoring for arrhythmia classification involves training ML models to accurately distinguish among different types of arrhythmias. Metrics such as training and validation accuracy, along with training and validation loss, are utilised to estimate the efficacy of these models. The training loss shows how well the model learns, but the validation loss demonstrates its performance on unseen data points. The training accuracy of the model shows its performance on the training data, while validation accuracy demonstrates its capacity to identify unknown ECG signals. The training process

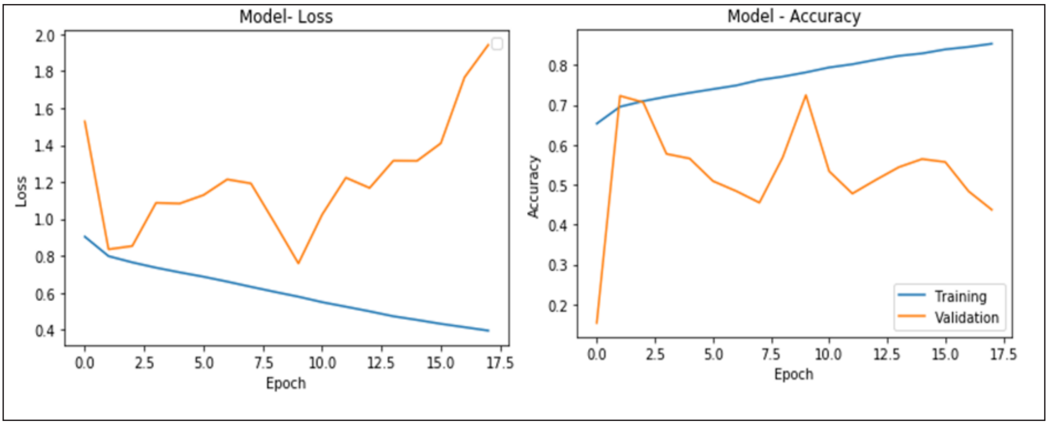

Figure 10. Training vs. validation loss and accuracy

allows users to monitor these performance indicators, which help them adjust the model for better results and improved arrhythmia organisation accuracy.

Table 6
10-fold Cross-Validation of ResNet-SMOTE-ENN Analysis

k-folds	**ResNet-SMOTE-ENN Accuracy**
1-fold	0.95
2-fold	0.97
3-fold	0.98
4-fold	0.98
fold-5	0.96
fold-6	0.97
fold-7	0.98
fold-8	0.98
fold-9	0.97
fold-10	0.98
10-fold mean	0. 97

Influence of SMOTE-ENN

The SMOTE-ENN algorithm proves its value because it enables improved model visualisation through its capability to manage unbalanced class distributions in data. ENN removes noisy cases by considering the nearest neighbours, while SMOTE generates synthetic examples for the minority class. This combined method improves the quality of the dataset, resultant in more accurate and reliable model forecasts, particularly in scenarios where class imbalance can significantly affect performance. SMOTE-ENN has proven to be effective in refining models by reducing overfitting and enhancing generalisation.

K-Fold Matrix

The application of 10-fold cross-validation significantly enhanced the consistency and resilience of the methods utilised in ECG monitoring for arrhythmia organisation. This statistical technique involves dividing the dataset into 10 segments, or subsets, where nine are used for training and one for validation. The proposed ResNet-SMOTE-ENN shows in Table 6 technique outperformed competing methods, achieving an accuracy of 97.84% on our input data utilising 10-fold cross-validation.

Comparison of the Proposed Model

Table 7 and Figure 11 present a comparison of accuracy across different methods and references for the MIT-BIH database. Swetha and Ramakrishnan (2021) achieved an accuracy of 91.50% using the KC-FLC technique. Essa and Xie (2021) improved performance to 95.81% by utilising Bagging Models, while Chen et al. (2020) reached 94.35% with the MACN+UDA approach, and Pokharel et al. (2024) achieved 96.71% accuracy using a CNN+ML Hybrid pipeline. Our proposed model, which combines ResNet with SMOTE-ENN, demonstrated the highest accuracy of 97.84%. The results demonstrate that ResNet-SMOTE-ENN outperforms traditional methods because it achieves better results.

Table 7
Comparison of the proposed model

Reference	Database	Method	Accuracy
Essa & Xie, 2021	MIT-BIH	Bagging Models	95.81%
Chen et al., 2020	MIT-BIH	MACN+UDA	94.35%
Swetha & Ramakrishnan, 2021	MIT-BIH	KC-FLC	91.50%
Pokharel et al., 2024	MIT-BIH	CNN + ML Hybrid Pipeline	96.71%
Our Model	MIT-BIH	ResNet-SMOTE-ENN	97.84%

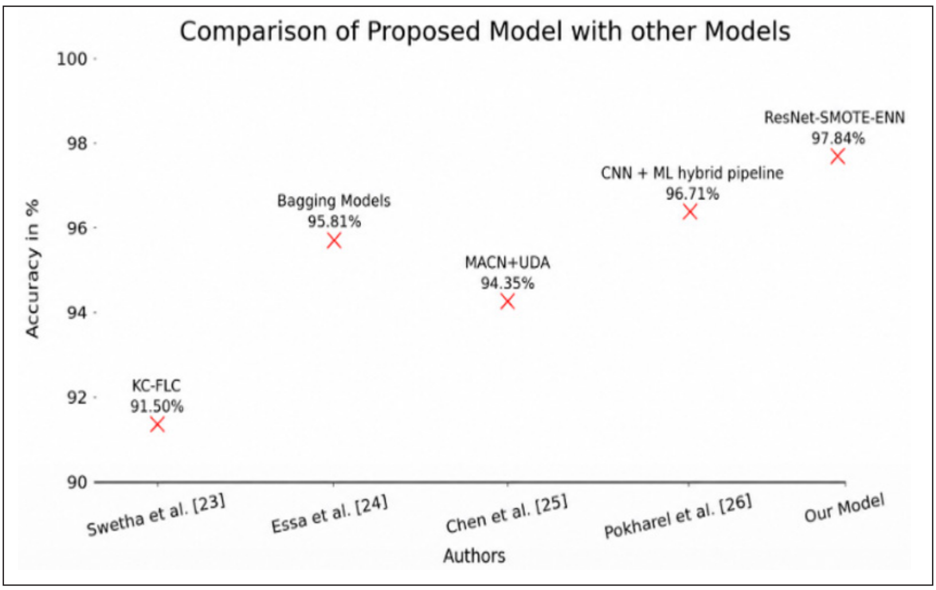

Figure 11. Comparison analysis of the proposed model with other models

Limitations

Despite the promising outcomes of utilising deep residual networks (ResNet) in conjunction with SMOTE-ENN for arrhythmia organisation, several limitations persist. First, SMOTE-ENN is heavily reliant on the amount and calibre of training data because the artificial data it produces frequently falls short of accurately capturing the intricacy of real-world ECG signals. The process of training deep neural networks requires significant computational resources, which leads to longer processing times and requires substantial hardware equipment. The method encounters two main difficulties when working with datasets that contain extreme imbalances between classes and outliers because SMOTE-ENN generates occasional noisy data points. The model maintains its ability to generalise data from the MIT-BIH database, but it needs additional training to work efficiently with different types of datasets.

CONCLUSION

The system, which uses deep residual networks with SMOTE-ENN methods, operates efficiently to analyse ECG data and identify arrhythmias. The hybrid approach solves two major problems which occur when ECG datasets contain unbalanced data and noisy information by creating a model which achieves better generalisation and higher classification accuracy. The proposed solution achieves better results than existing methods through its combination of SMOTE-ENN data balancing capabilities with deep residual networks' advanced feature extraction methods. The research demonstrates how this method functions as a dependable system which detects arrhythmias at their beginning stages for better clinical diagnosis. Future research should focus on two main areas, which include testing the system for real-time ECG monitoring and developing methods to merge the system with wearable health devices for ongoing patient monitoring.

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LIST OF ABBREVIATIONS

ECG	:	Electrocardiogram
ResNet	:	Residual Network
SMOTE	:	Synthetic Minority Over-sampling Technique
ENN	:	Edited Nearest Neighbours
ML	:	Machine Learning
DL	:	Deep Learning
NEB	:	Normal Ectopic Beats
VEB	:	Ventricular Ectopic Beats
SVEB	:	Supraventricular Ectopic Beats
LSTM	:	Long Short-Term Memory
bi-LSTM	:	Bidirectional Long Short-Term Memory
ROA	:	Rider Optimisation Algorithm
BaROA	:	Bat-Rider Optimisation Algorithm
MOBA	:	Multi-Objective Bat Algorithm
MRMR	:	Minimum Redundancy Maximum Relevance
ReLU	:	Rectified Linear Unit
FRM-CNN	:	Fusing Rhythmic Morphological-Convolutional Neural Network

MRFO-SVM	:	Manta Ray Foraging Optimisation-Support Vector Machine
AE-biLSTM	:	Auto- Encoder and Bidirectional Long Short-Term Memory
PVC	:	Premature Ventricular Contraction
APC	:	Atrial Premature Contraction
MCC	:	Matthews Correlation Coefficient
RMSE	:	Root Mean Square Error
MAPE	:	Mean Absolute Percentage Error
MACN	:	Multi-Attention Convolutional Network
UDA	:	Unsupervised Domain Adaptation
KC-FLC	:	Knowledge-Centric Fuzzy Logic Controller
CNN	:	Convolutional Neural Network
MIT-BIH Database	:	Massachusetts Institute of Technology–Beth Israel Hospital Database

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