ECG-Based Heartbeat Classification Using Convolutional Neural Networks

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***Abstract*—**Electrocardiogram (ECG) signal analysis and processing are crucial in the diagnosis of cardiovascular diseases which are considered as one of the leading causes of mortality worldwide. However, the traditional rule-based analysis of large volumes of ECG data is time-consuming, labor-intensive, and prone to human errors. With the advancement of the programming paradigm, algorithms such as machine learning have been increasingly used to perform an analysis on the ECG signals. In this paper, various deep learning algorithms were adapted to classify five classes of heart beat types. The dataset used in this work is the synthetic MIT-Beth Israel Hospital (MIT-BIH) Arrhythmia dataset produced from generative adversarial networks (GANs). Various deep learning models such as ResNet-50 convolutional neural network (CNN), 1-D CNN, and long short-term memory (LSTM) were evaluated and compared. ResNet-50 was found to outperform other models in terms of recall and F1 score using a five-fold average score of 98.88% and 98.87%, respectively. 1-D CNN, on the other hand, was found to have the highest average precision of 98.93%.

***Keywords*—**Heartbeat classification, convolutional neural network, electrocardiogram signals, ECG signals, generative adversarial networks, long short-term memory, LSTM, ResNet-50.

I. Introduction and Related Work

A. Introduction

ELECTROCARDIOGRAM signal analysis and processing are crucial in the diagnosis of cardiovascular diseases which are considered as one of the leading causes of mortality worldwide. Arrhythmia refers to the change in the rhythm of electrical impulses of the human heart [1]. This disturbance results in irregular heartbeats that may either be too fast, too slow, or too erratic compared to normal beat. A normal human adult heart rate ranges between 60-100 beats per minute and it is recorded using an ECG [2]. Worldwide, statistics show that 403 million suffered from this condition in 2017 alone and 17.6 million more people would likely have it by 2060 [3]. The main types of arrhythmia can either be classified as supraventricular, ventricular, or bradycardia depending on where the irregularity occurs. To determine the type of abnormal heart rhythm, an ECG analyzes the action impulse waveform of each tissue in the heart and then perform heartbeat segmentation [4]. ECG is a noninvasive diagnostic method that tracks the heart's physiological activity over time.

Many cardiovascular conditions can be detected using ECG data and they include congestive heart failure (CHF), premature contractions of the atria or ventricles, atrial fibrillation (AF), and myocardial infarction (MI) [5]. However, with the fast advancement of ECG equipment that consequently leads to an immense number of analyzed ECG data, examining a huge volume of these data consumes too much medical resources. In addition, they can be prone to human errors during analysis due to fatigue or continued usage over long periods of time. Therefore, the need for accurate, automatic and low-cost monitoring and diagnosis of heartbeats is highly desirable.

During the past few decades, numerous diagnostic systems based on machine learning (ML) techniques have been developed and proposed in the automatic analysis and diagnosis of cardiovascular diseases [6], [7]. With the development of this algorithmic paradigm, the application of ML offers the opportunity to significantly increase the accuracy and scalability of automated ECG analysis, which would aid cardiologists in making rapid and accurate diagnoses of ECG recordings while reducing the cost and time required for clinical interpretation.

B. Related Work

Numerous researches have focused on the use of ML algorithms for identifying aspects of an ECG signals as an attempt to overcome their issues. With the use of these techniques, data are automatically classified into a specific type of heartbeat. Neural networks (NN) are one of the methods that have been extensively explored. NN is a form of computational algorithm that consists of node layers capable of recognizing patterns and relationships in given data [8]. Due to this capability, the scientific community is still looking to utilize NN in various medical applications for automatic analysis.

Popular NN models including CNN, recurrent neural network (RNN), and gated recurrent unit (GRU) have been explored in analyzing ECG data. In fact, there has been a growing interest of research in the potential of CNN in ECG classification [9]-[13] as it has strong self-learning ability and provides exceptional automatic feature extraction [14]. A 1D-CNN, for instance, composed of three of each convolutional, max pooling and dense layers, was employed to classify the signals using the MIT-BIH arrhythmia database [15]. Based on five-fold cross validation, the model was able to achieve 97.36% and 99.83% of accuracy and F1 score, respectively. The same architecture and dataset were also studied where five layers were added to the input and output layer of the model consisting of two convolution and down sampling layers, and one fully connected layer [16]. The model was able to achieve

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a promising accuracy of 97.5%.

Zhang et al. [17] utilized RNN in learning the time correlation of ECG signal points where the morphology information such as T wave of the preceding and present beat were fed into the network. The model was able to achieve 98.7% and 99.4% in detecting supraventricular and ventricular ectopic beat, respectively. LSTM, a special type of RNN that mitigates the vanishing gradient problem [18], has been recently implemented in some studies [19]-[24] in the task of ECG classification. For instance, Singh et al. [20] implemented LSTM in distinguishing regular and irregular heartbeats and compared its performance with RNN and GRU and the results showed that LSTM outperformed the other models with 88.1% accuracy. Chauhan et al. [25] also achieved good accuracy using deep LSTM in classifying four types of arrhythmia without pre-processing the ECG signals. Likewise, Sujadevi et al. [26] compared the performance of RNN, LSTM, and GRU in detecting AF without using pre-processing, filtering, and denoising techniques. The results reported that RNN, LSTM, and GRU performed with 95.0%, 100%, and 100% accuracy, respectively. Liang et al. [27] combined a bidirectional model with 1D CNN to further improve the classification accuracy.

Along with the development of deep learning networks, more recent research has also focused on the use of state-of-the-art techniques such as Residual Neural Network (ResNet) [28]-[31], Visual Geometry Group Network (VGGNet) [32], and Densely Connected Convolutional Network (DenseNet) [33]. For instance, Jing et al. [34] proposed an improved ResNet-18 model where it used two different layers of ResNet, the classical ResNet-18 layer and the improved ResNet-18 layer where additional convolutional layers were applied. The proposed model was able to demonstrate superior performance over End-to-end Deep Neural Network (DNN) and 1D-CNN with its highest classification accuracy rate of 96.50%. Venton et al. [35] transformed the ECG signals into images and performed transfer learning using ResNet-50, AlexNet, and VGG-16 where ResNet-50 performed consistently well across the selected datasets with 0.65–0.71 F1 scores.

Ensembling of ML is another method used to improve ECG classification. Essa and Xie [36] created an ensemble model of CNN-LSTM and RRHOS-LSTM through the bagging method. The proposed meta classifier achieved an overall accuracy of 95.81% on the MIT-BIH arrhythmia dataset. CNN-LSTM combined three sets of convolutional and max-pooling layers with two LSTM layers, while RRHOS-LSTM integrated HOS and RR intervals features with LSTM. Weighted loss function was applied to resolve the high imbalance of data. Another paper used support vector machine (SVM), ANN, RNN, decision trees, and K nearest neighbor (KNN) for ensembling using voting method [37]. The model was tested on the PTB Diagnostic ECG and the MIT-BIT Arrhythmia dataset, finding improvements in performance with an 97.78% and 97.664% in accuracy respectively. The winning team for the PhysioNet Challenge 2021 created a three-model ensemble of residual CNNs composed of modified ResNet blocks with multi-head attention mechanism [38]. When tested on several datasets, the model achieved an overall score of0.58 for all lead configurations.

Data augmentation techniques have also been explored to improve the classification performance by increasing the size of training samples. Simple approaches include manipulating the time, frequency, or time-frequency domain. Combining patterns to create new data has also been performed in the past; this is more efficient in comparison to random transformations because it does not presume that data generated are quintessential of the data [39]. More advanced techniques made use of decomposition and statistical generative models, with learning-based methods embedding space and deep generative models. Such techniques are capable of imitating attributes of real data to create near-realistic products [40]. Recently, a deep generative model called generative adversarial network (GAN) has been employed to address the data imbalance issue in ECG dataset. This model works by producing new synthetic data instances where it involves the use of generator and discriminator [41]. One study that made use of GAN was conducted by Rath et al. [42] where they trained an LSTM model with a dataset augmented by GAN to address the imbalance of ECG samples by generating fake data. The proposed method achieved a striking accuracy and F1 score of 99.4% and 99.3% respectively. Shaker et al. [43] utilized GAN to address the imbalance issue on the ECG dataset and it was reported that classification performance can be boosted more efficiently by augmenting the dataset using GAN than using the same model that was just trained on the original dataset.

In this study, we propose various adapted methods of ECG based heart classification that make use of different NN models, specifically, 1D-CNN, LSTM, and ResNet-50. In addition, a synthetic dataset generated by 1-D GAN was used to train the previous models.

II. Materials and Methods

A. Dataset

The study used open-source ECG database from Kaggle repository which combined the training data of MIT-BIH arrhythmia database from [44] and synthetic data generated from 1D-GANs [45]. Testing data contained no generated samples. MIT-BIH arrhythmia database [46] from the Massachusetts Institute of Technology was used in this study. This database contains ECG signals with 48 recordings with each having a 30-minute recording time, and 360 Hz frequency. Recordings were obtained from 47 patients. As defined by the American Association for the Advancement of Medical Instrumentation (AAMI) [47], the annotations listed in Table I were grouped into five main categories, namely non-ectopic (N), unknown (Q), fusion (F), supraventricular ectopic (S), and ventricular ectopic (V). The examples of the ECG signals are shown in Fig. 1.

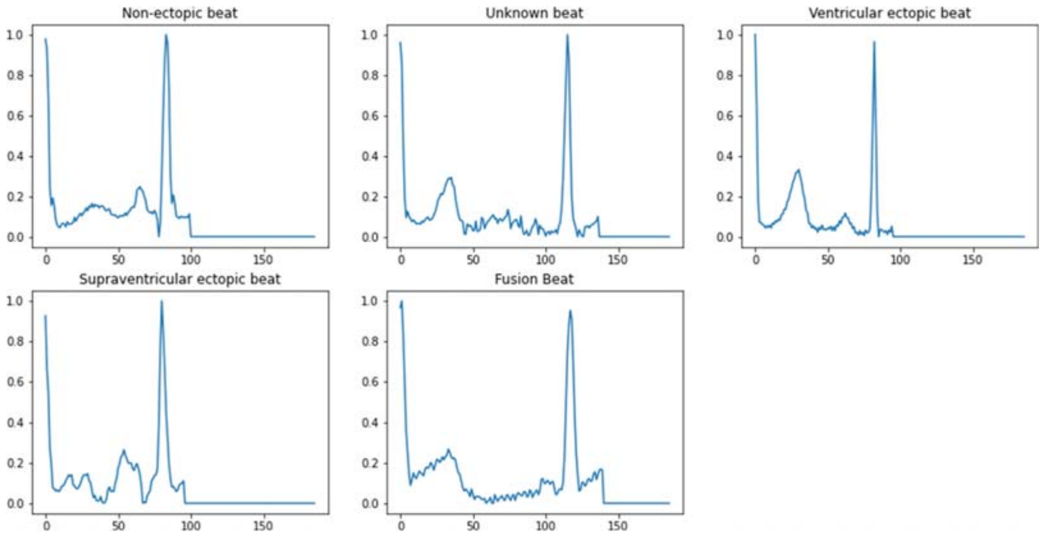

Fig. 1 Examples of ECG signals in each class

TABLE I
ECG BEATS CATEGORIZED AS PER AAMI

Class	Description	Annotation
N	Non-ectopic	Normal (NOR) Left bundle branch block (LBBB) Right bundle branch block beat (RBBB) Atrial escape (AE) Nodal (junctional) escape (NE)
Q	Unknown	Paced (P) Fusion of paced and normal (fPN) Unclassifiable (U)
F	Fusion	Fusion of ventricular and normal (fVN)
S	Supraventricular ectopic	Atrial premature (AP) Aberrated atrial premature (aAP) Nodal premature (NP) Supraventricular premature (SP)
V	Ventricular Ectopic	Premature ventricular contraction (PVC) Ventricular escape (VE)

B. Model Implementation

A synthetic 1D dataset was obtained from a Kaggle repository [45] where 1D GAN technique was utilized in the training set. The technique was used to generate more data for few insufficient labeled classes. Briefly, the architecture mainly consists of a bidirectional LSTM (BiLSTM) generator and discriminator. The generator synthesizes data using Gaussian-distributed sampled noise data points and learns from the discriminator's feedback. The discriminator, on the other hand, determines whether the generated data are real by learning the probability distribution of the original data and providing a true-or-false value. It should be noted that the dataset was divided into training and testing sets in an 80:20 ratio before GAN was applied on the training set.

Initially, a total of 109449 data comprised the dataset with the N class dominating with 90589 data points and the S class and F class as the least with 2779 and 803 data points, respectively. After the process, the total number of datapoints were increased, most especially with the S and F class whose data points increased to 4958 and 2150, respectively. This method was implemented to validate the efficiency of the model with a slightly higher number of training sets in classes S and F specifically. Figs. 2 and 3 show the difference between two datasets before and after GAN was applied as well as the sample results obtained before and after the process, respectively.

C. Overview of the Proposed Models

This study examined the classification performance of three NNs, namely 1D-CNN, LSTM, and ResNet-50. All models were trained with a dataset of GAN based augmented ECG signals. For training, all proposed models used Adam optimizer with a learning rate of 0.0001. The models' batch size was set to 64 and the number of epochs was 25. An early stopping was applied to stop the training when the model stops improving and lean towards overfitting on the validation set. For the loss function, a categorical cross-entropy was utilized which is generally appropriate for the classification of multiple classes. The implementation of the algorithms used were accomplished in Colaboratory^{TM} by Googleusing its built-in GPU (NVIDIA® Tesla® K80) setting.

1-D CNN

1-D CNN is suitable for time series data wherein one-dimensional arrays are analyzed as feature extraction and classification operations are merged into one process [48]. Because they are simpler by architecture, there is the benefit of less computational cost while still maintaining high performance. The proposed model only contains two convolutional blocks, two fully connected layers and a soft-max layer. The convolutional block was composed of layers of convolutional, rectified linear unit (ReLU), and max pooling. Batch normalization layers were added after the ReLU layers in each convolutional block to normalize the input layer. The max pooling layer was then flattened. Dense layers were then added followed by a drop-out layer of 0.5 to avoid overfitting. An activity regularizer is specified on each dense layer where L2 regularization of 0.0001 was applied. The softmax function was utilized to generate prediction probability over five output classes.

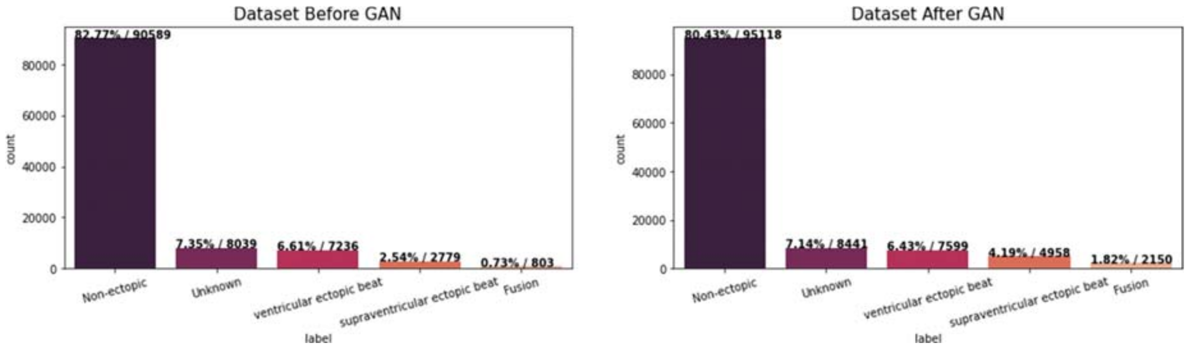

Fig. 2 Difference between two datasets before and after GAN was applied

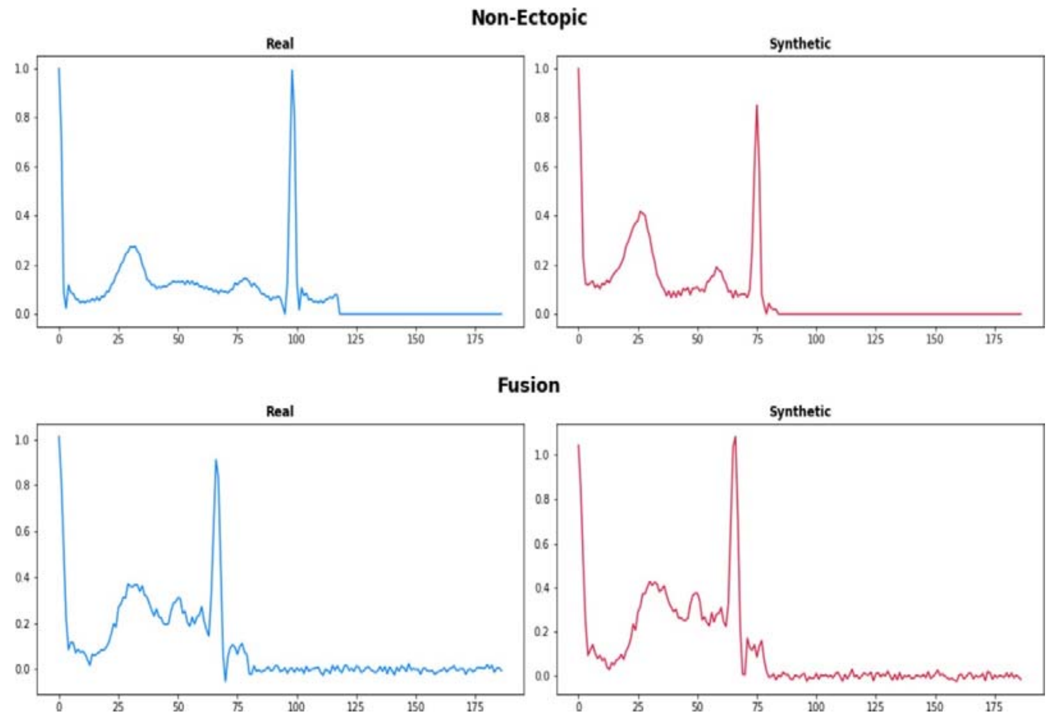

Fig. 3 Sample real and synthetic ECG signals

Fig. 4 Network Architecture of 1D-CNN

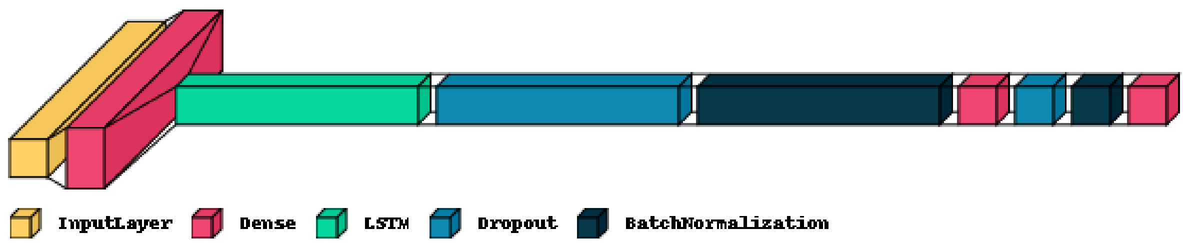

Fig. 5 Network Architecture of LSTM

RNN is capable of handling long time dependencies and solving vanishing gradient problems [49]. It is well-suited to process, classify, and make predictions based on time series data [50]. The proposed model begins with a dense layer and is followed by the LSTM layer with 128 neurons. An activity regularizer is also specified on each dense layer where L2 regularization of 0.00001 was applied. Two dropout layers of 0.5 were then applied after each dense layer which was then followed by batch normalization. For the activation function, the nonmonotonic, smooth function known as Swish was applied.

ResNet-50

ResNet, at its core, allows for the use of the skip connection concept in order to address the problem of vanishing gradients. This is achieved through the implementation of larger layers without compromising the accuracy rate. As adapted from [51], the architecture is mainly composed of multiple residual blocks, convolutional blocks and identity blocks in particular, which each contain a convolutional layer, a batch normalization layer, and ReLU activation function. Briefly, the model begins with 1x1 convolutional layer, batch normalization, ReLU, and max pooling. This is followed by multiple convolutional blocks where each of these blocks is accompanied with 2,3,5,2 identity blocks. The convolutional block has skip connections that allow the flow of gradient from the initial layer to the final layer. Average pooling was done before flattening the layer. Dense layers were then added and finally the SoftMax function was used to generate the output. The total number of parameters was 17,839,109.

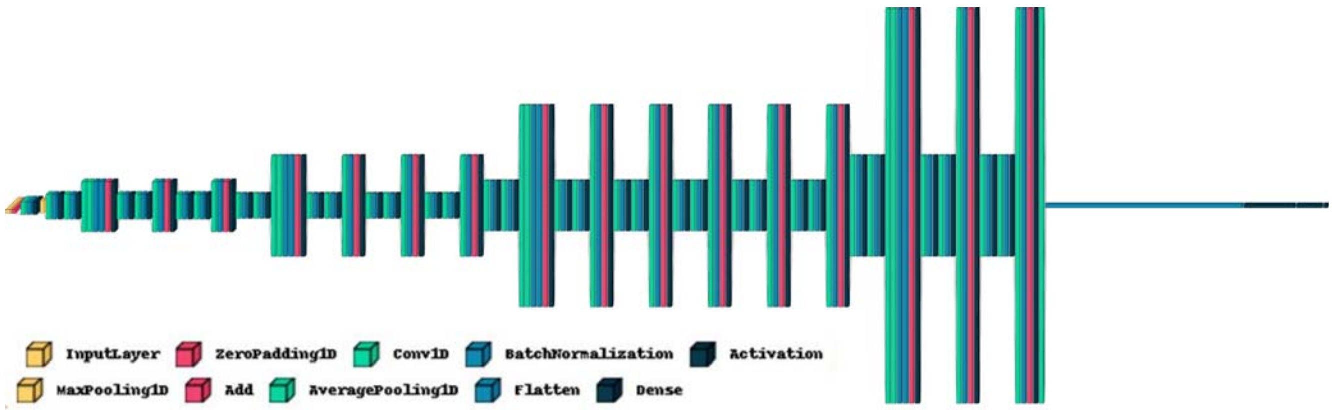

Fig. 6 Network Architecture of ResNet-50

D.Performance Evaluation

A five-fold cross validation (*CV*) was performed to evaluate the performance of the model through its average precision (*P*), recall (*R*) and F1 score (*F1*). This was done where the models were run five times. A confusion matrix was also used to describe the classification performance by categorizing their results to show how many beats were correctly classified or misclassified into five classes of heartbeats. Performance indices that provide for these values include true positive (*TP*), false positive (*FP*), true negative (*TN*), and false negative (*FN*).

The summary of the standard measurements are as follows:

Precision refers to the heart beats predicted correctly of one class over the sum of all heart beats predicted with this class:

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

Recall refers to the correctly classified heart beats of once class over the sum of heart beats belonging to that class:

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

F1 score refers to the harmonic mean of the precision and sensitivity of the ECG classification

III. Results and Discussion

Experiments were done using the synthetic dataset utilized to train and evaluate the proposed models, namely 1D-CNN, LSTM, and ResNet-50. Each model was run five times resulting in five results of each metric. The three sets of tables show the precision, recall, and F1 score results of these models where the weighted average of each metric was presented. The standard deviation was also calculated for each metric across three models. The confusion matrix of each model was presented in Fig. 7.

TABLE II
Comparison between 1DCNN, ResNet50, and LSTM in Terms of Precision

Run	LSTM (baseline)	1D-CNN (proposed)	ResNet-50 (proposed)
1	96.04	98.87	98.88
2	96.78	98.95	99.01
3	96.58	98.93	98.70
4	96.45	98.99	98.93
5	96.03	98.90	98.87
Mean	**96.38**	**98.93**	**98.88**
STD	**0.33**	**0.05**	**0.11**

Precision or the positive predictive value measures the heart beats predicted correctly of one class over the sum of all heart beats predicted with this class - it provides the probability of accurate prediction of the network. In Table II, 1D-CNN was found to have the best classification performance in terms of precision (98.93 0.05%). It also exhibited the lowest variance; this indicates that the model exhibited more consistency in performance.

TABLE III
COMPARISON BETWEEN 1DCNN, RESNET50, AND LSTM IN TERMS OF RECALL

Run	LSTM (baseline)	1D-CNN (proposed)	ResNet-50 (proposed)
1	94.58	98.74	98.89
2	90.26	98.84	**99.02**
3	**95.19**	98.73	98.70
4	94.30	**98.97**	98.94
5	94.48	98.84	98.87
Mean	**93.76**	**98.83**	**98.88**
STD	**1.99**	**0.10**	**0.12**

Recall or sensitivity measures the correctly classified heart beats of once class over the sum of heart beats belonging to that class, thereby, reflecting the ability of the model to detect different heart beats that will aid in detecting ECG abnormalities. In Table III, it is shown that the ResNet-50 performed best in classifying the heartbeats correctly with an average recall of 98.88, followed by 1D-CNN with a small margin. The LSTM obtained the lowest sensitivity value with 90.26, indicating that there are some ECG signals that were misclassified.

F1 score measures the harmonic mean of precision and recall. This index describes the capability of recognizing heart signals. Based on Table IV, ResNet-50 obtained the highest average F1-score, thereby demonstrating good generalization performance. 1D-CNN does not measure far from this with a 0.01 mean F1 score difference. With an observed lower standard deviation, 1D-CNN is also considerably better in terms of F1 score.

TABLE IV
COMPARISON BETWEEN 1DCNN, RESNET50, AND LSTM IN TERMS OF F1 SCORE

Run	LSTM (baseline)	1D-CNN (proposed)	ResNet-50 (proposed)
1	95.04	98.78	98.88
2	92.90	98.88	**99.00**
3	**95.65**	98.79	98.69
4	95.02	**98.98**	98.93
5	94.98	98.86	98.87
Mean	**94.72**	**98.86**	**98.87**
STD	**1.05**	**0.08**	**0.16**

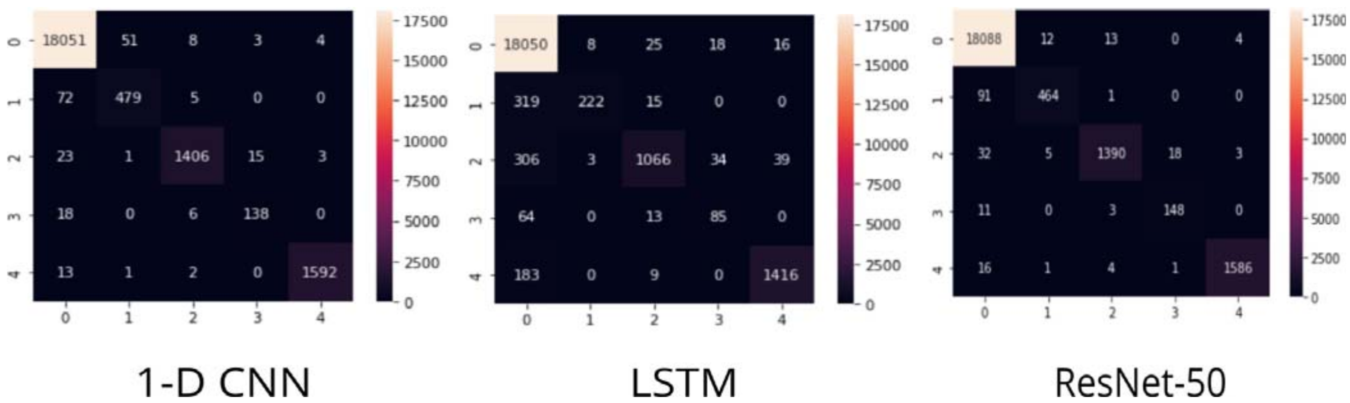

Fig. 7 The Confusion Matrix of Three NN s. The heartbeats are classified into five types: non-ectopic beat (0), supraventricular ectopic beat (1), ventricular ectopic beat (2), Fusion beat (3), and unknown beat (4)

Fig. 7 describes the performance of the models through a confusion matrix where each of the results of the models that are shown was selected based on the best results of F1 score. Based on the figure, it appears that fusion beats are often misclassified across three models where the LSTM model managed to correctly classify 85 beats out of 162 beats. Most of these beats were misclassified as normal beats. The LSTM model performed poorly in detecting supraventricular ectopic beats where it misclassified the beats as normal beats. This may be attributed to the fact that many signals in the Class S have a similar wave characteristic to that of Class N where the major difference between the two classes lies in the absence of the P-wave and the change of RR interval [52]. Among three models, the ResNet-50 model performed best in classifying the beats as reflected in its F1 score shown in Table IV. Findings support the higher capacity of CNNs that led to its prevalence in recent ML research. 1D-CNN and ResNet-50 measured closely in the following metrics with 1D-CNN having slightly lower values but lower variance while ResNet-50 performed the best but exhibited higher variance.

IV. CONCLUSION

The study presented in this paper demonstrated an application of ECG based heartbeat classification using ML models. A synthetic dataset produced by 1D-GAN was used to train and evaluate the models. The results from the proposed models including ResNet50, 1D CNN, and LSTM highlight the superior performance of CNNs. The results show superior performance of the proposed method of CNN compared to baseline of LSTM in terms of F1 score. The proposed solution can help to automate ECG signal classification to reduce time, labor, and human errors.

The obtained results confirm the possibility to use such models in assisting ECG analysis. However additional studies using increased real ECG data and an evaluation of other ML techniques are highly recommended. The use of GANs for exploring other medical analysis tasks is also encouraged in tackling the common challenge of limited datasets.

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DECLARATION OF COMPETING INTEREST

All authors declare to have no competing interests.

DATA AVAILABILITY

The Dataset belongs to:

- S. Fazeli: https://www.kaggle.com/datasets/shayanfazeli/heartbeat
- M. Polo: https://www.kaggle.com/datasets/polomarco/mitbih-with-synthetic

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