A Gan-Driven Deep Learning Framework for Cardiac Arrhythmia Classification

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***Abstract*—Accurate detection and classification of heart rhythm disorders are crucial in modern medical care. Untreated or inappropriately diagnosed heart rhythm disorders can lead to life-threatening complications like stroke, heart failure, or sudden death. Conventional methods of Electrocardiogram (ECG) analysis are mostly dependent on medical professionals interpretations. This not only consumes time but is also fraught with possibilities of diagnostic inaccuracies. A common issue in the publicly available MIT-BIH Arrhythmia database is that the number of normal heartbeats is imbalanced with supraventricular, ventricular, fusion, and unknown heartbeats [4]. This paper presents an AI-based arrhythmia classification system that utilizes deep learning and data augmentation techniques. Using the Generative Adversarial Network (GAN) approach for generating the minority class of ECG signals, the dataset gets balanced, thus helps in increasing the accuracy of the classifiers [1]. Once this happens, the process uses the combination of Convolutional Neural Networks (CNN) , Long Short-Term Memory (LSTM), for data analysis. Each heartbeat is categorized into five different categories like normal, supraventricular, ventricular, fusion, and unknown. These categories can then be mapped into different clinical labels like bradyarrhythmia, tachyarrhythmia, and normal rhythm. This proposed system is designed for fast, reliable arrhythmia diagnosis.**

***Index Terms*—Cardiac Arrhythmia, Heartbeat Classification, Electrocardiogram, Deep Learning, Generative Adversarial Network.**

I. INTRODUCTION

Cardiac arrhythmia, an irregular heartbeat condition, has emerged as a global health issue in recent years [1]. Detection and characterization of arrhythmias in real time become mandatory in preventing fatal complications like stroke, heart failure, and sudden cardiac arrest [5]. The traditional approaches to diagnosis highly depend on human interpretation of the electrocardiogram (ECG) signal by doctors, which is time-consuming and susceptible to human error [9].

Electrocardiogram (ECG) is an essential diagnostic tool that captures the time course of the electrical activity of the heart [4][7]. It offers useful information regarding cardiac rhythm, conduction defects, and structural or functional defects [3]. ECG analysis is now an integral component of early disease detection and management of the patient in hospitals and remote monitoring systems alike. Manual interpretation of ECG traces is, however, time-consuming and requires much skill and may be inconsistent in the presence of large datasets[9].

Furthermore, the unevenness (or) unbalanced nature of the readily available ECG datasets with abundant instances of the normal beat compared to the abnormal one diagnosis. Also, public data such as MIT-BIH hinders the efficacy of classical characterization systems and makes them less effective in detecting the sparse instances of the event in question [8].

To correct such limitations, the present work proposes an advanced deep-learning model known as "A GAN-Driven deep learning framework for cardiac arrhythmia Classification". The model employs Generative Adversarial Networks (GANs) in order to generate new ECG signals for under-represented classes and improve the balance of the datasets and the model's performance.

The datasets thus generated are then utilized with hybrid classifiers such as Convolutional Neural

Networks (CNNs), Long Short-Term Memory (LSTMs), and Random Forests [10]. The model strives to create an accelerated, credible, and automated technique for the detection of arrhythmia such that diagnostic delay remains minimal and effective data-driven cardiac health analysis is made easier [1][6].

II. RELATED WORK

Cardiac arrhythmia detection and accurate classification plays a vital role within the contemporary healthcare system due to possible detrimental effects associated with undiagnosed or incorrectly labeled arrhythmias. Conventional ECG processing involves considerable expertise from healthcare practitioners. However, such systems involve considerable processing time for experts and usually result in inaccurate diagnosis. Also, public data such as MIT-BIH usually presents an unequal distribution where regular heartbeats substantially outnumber supraventricular, ventricular, fusion, or unknown heartbeats [4].

Advances in machine learning and deep learning have resulted in the introduction of arrhythmia detection systems that have the ability to learn patterns from ECG signals. In the early stages of machine and deep learning technology, Logistic Regression, Decision Trees, Random Forest Classifiers, and the k-Nearest Neighbor Classifier have already been used successfully using hand-crafted features that consider the RR and QRS durations and the amplitude variations in ECG signals [4]. Though accurate and efficient, the above-mentioned techniques lack the capacity to learn complex patterns from ECG signals.

Methods using deep learning techniques, especially CNNs or LSTMs, have greatly enhanced the accuracy level of arrhythmia classifiers by learning features at different levels directly from the raw signals of the ECG itself [5][6]. Hybrid architecture GAN-Assisted CNN-BiLSTM-Attention networks, overcome the problem of class imbalance using data synthesis [5]. Other sophisticated approaches include Spectrogram transformations using SLT, residual learning, or fusion learning using multiple signals, including both ECG and PPG, to enhance accuracy [3][10].

Nevertheless, certain difficulties are also present in the field despite the high level of innovation. The requirement for extensive computational resources by deep leaning models, along with the difficulty in interpretations by these models, might affect the efficiency of lightweight models/single-lead models to some extent by sacrificing the accuracies [7]. Noise, electrode movement, and physiological differences in the ECG signal make classification more challenging in the case of real-world ECG signals.

Based on these findings, the proposed system adopts a GAN technique for generating minority classes of ECG data. This helps alleviate the imbalance issue and subsequently enhances the performance of the classifier algorithm. The system combines the use of CNNs and LSTMs. In this model, heart rates are classified based on categories that include normal, supraventricular, ventricular, fusion, and unknown. The above classes can be translated to other clinical classes that include bradyarrhythmia, tachyarrhythmia, and normal rhythm. This is done using the hybrid model that is AI-powered. The system can be used for fast and accurate diagnostic results for arrhythmia. It can also be portable.

III. METHODOLOGY

The suggested model presents an intelligent AI-enabled system for automated detection and classification of cardiac arrhythmias with ECG signals. The protocol starts with data preprocessing where raw ECG signals of the MIT-BIH Arrhythmia database are filtered to eliminate noise, baseline drifts, and motion artifacts. Preprocessed ECG waveforms undergo segmentation into separate heartbeat windows and labeled in accordance with AAMI specifications. Preprocessed segments are retained in the database of the system and acted upon for successive analysis and classification. The system encompasses Convolutional Neural Networks (CNNs) for automated feature extraction, Long Short Term Memory (LSTM) networks for learning of time sequences, and Random Forest (RF) classifiers for ensemble-based prediction.

To counter the issue of class imbalance, Synthetic ECG beats for under-represented arrhythmic classes like supraventricular and ventricular beats are generated with the help of a Generative Adversarial Network (GAN). The generator develops plausible signals of heartbeat imitating the structural morphology of real ECG traces, and the discriminator maintains authenticity with the aid of adversarial learning. The resultant synthesized data thus obtained are combined with the actual dataset and used to create a balanced and inclusive training set for the deep learning models.

During training of the model, the CNN, LSTM classifiers are tested on several data splits like 60:40, 70:30 and 80:20 in order to be robust and consistent in their performance. The outputs of the classification are evaluated in terms of accuracy, precision, recall, and macro F1-score. After the detection of an abnormal heartbeat by the model, it classifies it into any one of the five AAMI categories (Normal (N), Supraventricular (S), Ventricular (V), Fusion (F), or Unknown (Q)) and maps them to the actual clinical condition like bradyarrhythmia or tachyarrhythmia or normal.

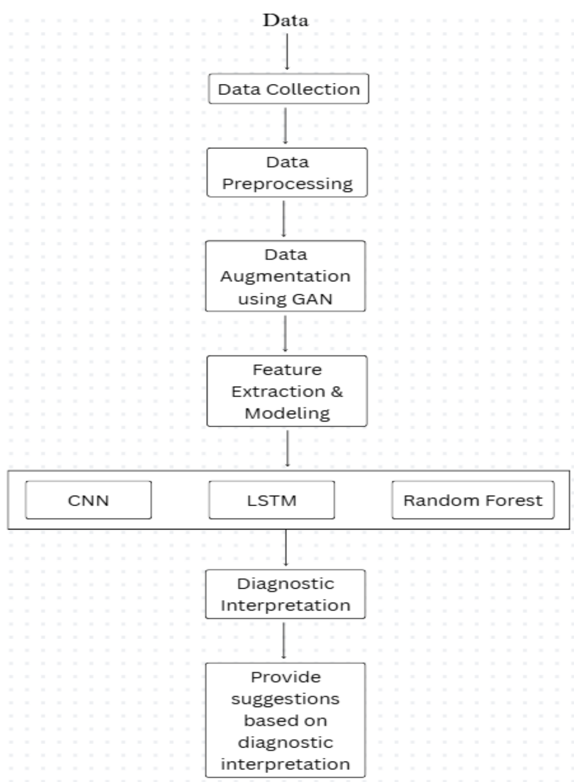

Figure 1. Process flow of the proposed model

Figure 1 shows the process flow of the proposed model with the data augmentation with GAN and data training with various algorithms like CNN and LSTM. The system proposed improves diagnostic accuracy, minimizes the rate of false detection, and helps doctors in the early cardiac risk assessment.

IV. PROPOSED SYSTEM

The most recent system diagnoses and classifies cardiac arrhythmias from ECG signals using artificial intelligence. The noise is eliminated by preprocessing and the ECG data are divided into individual heartbeats. Generative Adversarial Networks (GANs) produce new synthetic instances for the minority classes of heartbeats for balancing the data. A Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) network or Random Forest (RF) model classifies the balanced dataset. Every individual heartbeat is classified under the type of Normal, Supraventricular, Ventricular, Fusion, or Unknown type and aids early cardiac abnormality detection for greater reliability and accuracy.

A. Architecture of the system

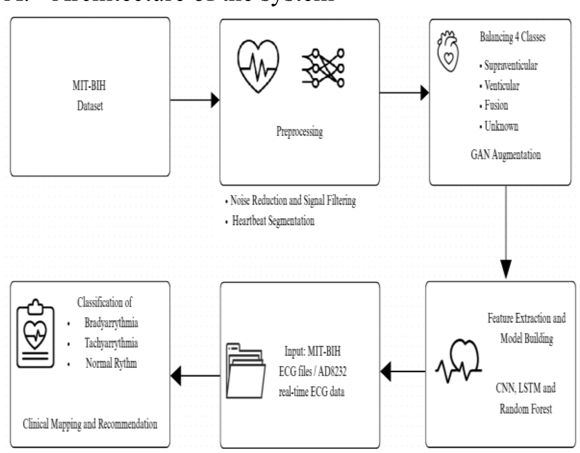

Figure 2. Architecture of the model

As shown in Figure 2, the introduced model begins by obtaining the ECG data from the MIT-BIH Arrhythmia Dataset to be the foundation for analysis and classification. The signals are also subjected to the preprocessing stage where the noise and the drift of the baseline are removed and each heartbeat is extracted for further analysis. After preprocessing, the dataset undergoes the GAN augmentation module where all the five heartbeat classes like Normal, Supraventricular, Ventricular, Fusion, and Unknown are all balanced by the addition of realistic synthetic instances for the minority classes as shown in the Figure 7.

The balanced data are further utilized for training the CNN, LSTM, or Random Forest models wherein feature extraction and learning of the model occur for the purpose of recognizing unique patterns for each type of heartbeat and the LSTM turned out to be the best model as shown in Figure 5.18. Following the training of the model, classification and clinical mapping are undertaken wherein the model assigns each beat to the respective category like Bradyarrhythmia, Tachyarrhythmia, or Normal Rhythm. Finally, recommendations for diagnosis are given by the system using the classification result where healthcare professionals are assisted by accurate automated cardiac evaluation.

B. Module Design

Dataset Acquisition
- Get labeled ECG datasets like MIT-BIH Arrhythmia.
- Sample should include all types of heartbeats (normal, supraventricular, ventricular, fusion, unknown).
- Record class imbalance to rectify the same in subsequent stages.

Preprocessing
- Denoise using a band-pass filter (0.5–50 Hz) for eliminating baseline wander, powerline noise, and high-frequency noise.
- Identify R-peaks from the ECG signals.
- Split individual heartbeats into fragments surrounding the R-peak and normalize or pad them to a predefined length to make them uniform.

Data Augmentation.
- Pull minority classes from data.
- GAN-based augmentation to artificially create ECG signals for minority classes.
- Keep the augmented dataset balanced so the model can train better.

Feature Extraction and Model Building
- Construct deep learning models for automatic learning of ECG signal features.
- Use CNNs for spatial patterns and LSTMs for temporal patterns recognition.
- Use a Random Forest classifier as an optional baseline non-deep model, if necessary.
- Train the classifiers to classify the single heartbeat's class into one of five classes: normal, supraventricular, ventricular, fusion, or unknown.

Classification and Clinical Mapping
- Map predicted heartbeat classes onto clinical conditions like bradyarrhythmia, tachyarrhythmia, or normal rhythm.
- Establish cutoffs or thresholds for clinical interpretation and possible interventions.

The developed system consists of several modules that can be operated concurrently for the proper detection, classification, and interpretation of cardiac arrhythmia. This process proceeds with the data acquisition module that captures the ECG signals from the MIT- BIH Arrhythmia Dataset, a popular standard dataset for arrhythmia. The raw ECG signals so acquired are fed into the preprocessing module where several signal enhancement methods like elimination of noise, removal of the baseline drift, and segmentation of the heartbeat are utilized. This ensures that model training and testing are done using-clean, properly organized, and regular ECG data.

In order to overcome the challenge of dataset imbalances, the GAN augmentation module is crucial in that it supplies synthetic instances of ECG for sparsely represented arrhythmic classes such as Ventricular and Supraventricular beats. The synthesized instances are realistic and statistically indistinct from true ECG instances and therefore improve the distribution of the classes and help in training the model in a balanced manner. This aspect of augmentation helps the system become more sensitive and robust and particularly for the less frequently represented types of arrhythmia that are most often under-detected by the typical models.

After balancing the dataset as shown in the Figure 7 the training module for the model is utilized to train the system by running any of the three algorithms such as Convolutional Neural Network (CNN) for extracting space features, Long Short-Term Memory (LSTM) for sequence-based temporal learning, or Random Forest (RF) for ensemble classification. The models are assessed by using the performance measures such as accuracy, precision, recall, and F1-score. The classifier's output is further fed to the clinical mapping module that translates the classified beats into the clinical conditions such as Bradyarrhythmia, Tachyarrhythmia, or Normal Rhythm. The final stage aids the doctors by providing accurate and reliable insights to help them diagnose cardiac abnormalities accurately.

V. IMPLEMENTATION

Figure 3 shows MIT-BIH Arrhythmia Dataset, which is a normal electrocardiogram (ECG) data collection commonly used for research into heartbeat and arrhythmia classification. It contains 48 half-hour ECG recordings from 47 patients, sampled at 360 Hz, with a total size of approximately 266 MB of data. All the heartbeats are classified into five broad classes, They are N , S, V, F, Q in accordance with the Association for the Advancement of Medical Instrumentation (AAMI) standards. Because of its stability and standardized annotations, this dataset is widely used in developing, training, and testing machine learning and deep learning models, and it remains one of the most authoritative standards in cardiac signal analysis and arrhythmia detection research.

0	1	2	3	4	5	6	7	8	9	...	186
0.0231	0.0173	0.0138	0.0130	0.0140	0.0149	0.0140	0.0117	0.0109	0.0147	...	0.0423
0.0935	0.1023	0.1053	0.1029	0.0975	0.0922	0.0887	0.0868	0.0851	0.0822	...	0.0865
0.0748	0.0823	0.0912	0.0994	0.1047	0.1058	0.1036	0.1005	0.0982	0.0963	...	0.1028

Figure 3. MIT-BIH Arrhythmia Dataset

A. Technologies Used

The software system runs under Python for model construction and primary logic. TensorFlow and the Keras libraries are employed for constructing and training the deep models, while the Pandas and NumPy libraries are utilized for data manipulation and preprocessing. Matplotlib and Seaborn libraries are employed for displaying class distributions, loss curves, and evaluation measures. Django is applied for web-based deployment and result presentation purposes while using the frontend interfaces defined in terms of HTML5 and CSS3. SQLite3 is utilized for the database that retains the ECG data and the results of the classification.

B. Model Building

i. GAN based Augmentation

There are some classes of arrhythmia in the ECG heartbeat dataset that are far less common than the normal beats, and therefore the problem is class imbalance on a very high scale. Standard oversampling methods such as SMOTE are not considered because they do not address temporal and physiological relationships of ECG signals and generate overfitting or even spurious patterns. To address this, a Generative Adversarial Network (GAN) was utilized to generate minority class ECG signals, which created an evenly balanced dataset of samples in all classes.

The project utilizes a Wasserstein GAN with Gradient Penalty (WGAN-GP) an enhanced version of vanilla GAN that stabilizes training using the Wasserstein distance as a loss function rather than the Jensen–Shannon divergence. Generator network is learned to generate high-quality ECG waveforms from noise, and the critic (or discriminator) is learned to differentiate between real and generated signals as shown in Figure 4. The gradient penalty enforces smoothness constraints such that the critic will not overfit and will converge stably even with low-data.

At training, the generator is utilized to enrich minority classes by generating artificial ECG signals that mimic the actual waveform in terms of amplitude and shape. The artificially generated samples are added into the genuine dataset to create a comprehensive balanced training set. After training classifiers like CNN or LSTM using this balanced data, they are observed to perform better especially in identifying less common types of heartbeats and have better macro F1-scores and overall better generalization across classes.

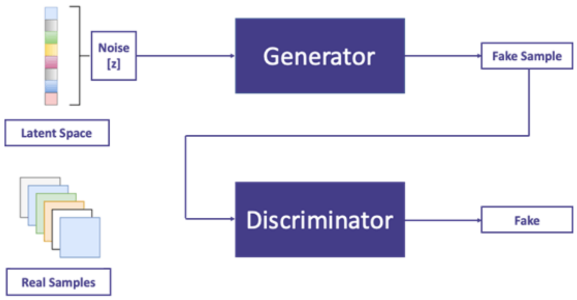

Figure 4. GAN Architecture

ii. Convolutional Neural Network

CNN algorithm self-learns the spatial features of the ECG waveforms. Local patterns such as the P-wave, QRS complex, and T-wave are identified by the convolutional layers. Pooling layers reduce the number of dimensions and help preserve salient details. Dense layers in the last stage are employed for the classification of the beats in one of the five arrhythmia classes. CNN minimizes human intervention for feature extraction and attains high accuracy and scalability for the analysis of the ECG signal.

The CNN model has been implemented in the form of a 1D convolutional architecture (SimpleCNN1D) for processing sequential ECG waveforms.

It is composed by three convolutional blocks:

- The first layer applies a 1D convolution operation over 32 filters of 7 to recognize the low-level patterns of waveforms such as the QRS complexes and the P-wave.
- The second level expands the depth of the features to 64 channels by a 5x5 kernel for increased mid-level abstraction.
- The third level applies 128 filters of kernel size 3 and applies an adaptive average pooling operation for compaction of spatial dimensions into a unique representative feature vector.

A fully connected (linear) layer is then used to project the learned 128-dimensional feature vector to the five-neuron-containing output layer where each neuron is associated to a class of heartbeat as shown in Figure 5. Non-linearity is implemented using the ReLU (Rectified Linear Unit) activation function and the employment of MaxPooling after every convolution serves to reduce the feature dimension while preserving salient details. The network has a light- weight but effective model for the feature extraction of spatial features from ECG signals.

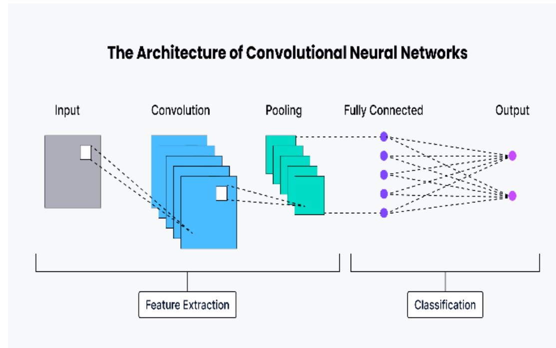

Figure 5. CNN Architecture

iii. Long Short-Term Memory

LSTM model as shown in the Figure 6 considers the ECG signal as time series sequences. It has the ability to discover long-range time patterns through its memory cells and discern rhythm irregularities extending over a series of beats by the virtue of a gating mechanism. It performs very well when observing time, but not waveform-shaped, arrhythmias and also has good sequential analysis performance for cardiac data.

The LSTM model (LSTM1D) is designed to capture temporal dependencies in ECG sequences. Unlike CNN, which focuses on spatial waveform patterns, LSTM learns how ECG values evolve over time.

The network functions are:

- Single LSTM layer of 128 hidden units that includes the flag for the optional bidirectional support so that the model will be able to find the sequence's backward and forward dependencies.
- Each ECG signal is transposed from shape [Batch, Channels, Length] to [Batch, Length, Channels] to fit the PyTorch LSTM input format.
- The final step output of the sequence is fed into a linear classification head that passes the hidden state representation to the five classes of heartbeat.

The model utilizes memory cells and gates (input, output, and forget gates) for the maintenance of long-term context that plays a crucial role in recognizing arrhythmias such as Supraventricular or Ventricular beats that are dependent upon the continuity of the rhythm for several heart cycles.

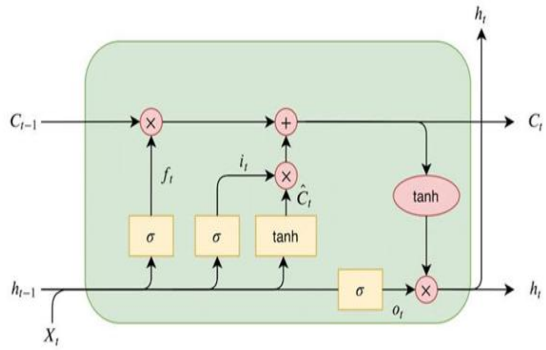

Figure 6. LSTM Architecture

VI. RESULTS AND DISCUSSIONS

The implemented modules are shown in the form of results with the raw data and balanced data before and after augmentation of data respectively and compared the models of CNN and LSTM with 60:40, 70:30 and 80:20 splits and finding the best model to detect and classify the condition of cardiac arrhythmia accurately by using few performance measures like accuracy, precision, recall and confusion matrix

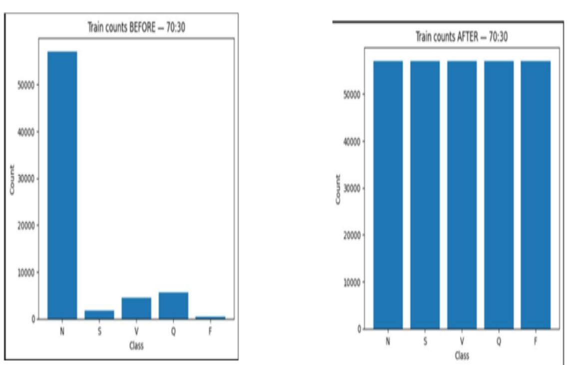

Figure 7.Class distribution before and after balancing

Figure 7 shows a clear class imbalance before and after GAN based balancing respectively.

Split Ratio	Raw Accuracy	Balanced Accuracy	Raw F1	Balanced F1	epochs
60:40	0.962	0.956	0.799	0.802	30
70:30	0.966	0.969	0.829	0.852	30
80:20	0.965	0.963	0.829	0.829	30

Figure 8 CNN RAW vs Balanced for different splits

Figure 8 is a plot of SimpleCNN1D metrics at 30 epochs for all splits (60:40, 70:30, 80:20) and RAW vs GAN-balanced data. Balancing enhances performance, and the highest F1-Macro is achieved by the 70:30 split.

Split Ratio	Raw Accuracy	Balanced Accuracy	Raw F1	Balanced F1	epochs
60:40	0.943	0.978	0.647	0.893	30
70:30	0.979	0.980	0.896	0.898	30
80:20	0.976	0.979	0.884	0.897	30

Figure 9 LSTM RAW vs Balanced for different splits

Figure 9 indicates that the balanced data of LSTM model does the best with the best F1 score (0.898) and Accuracy (0.980) at 30 epochs.

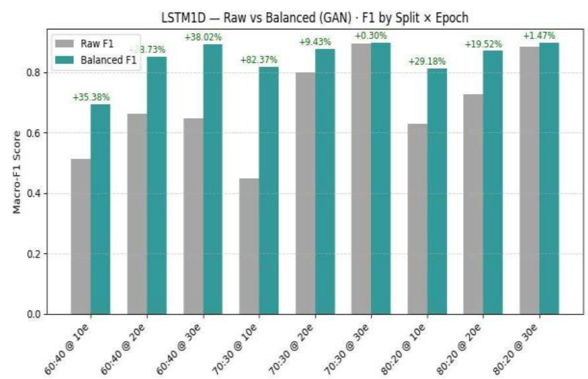

Figure 10. Plot of LSTM1D F1-Score Improvement

Figure 10 illustrates Macro-F1 scores of LSTM1D on raw vs GAN-balanced data. Gray bars are raw, teal bars are balanced, and labels indicate the percentage improvement by balancing.

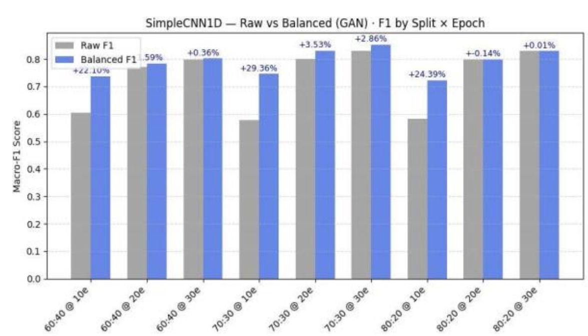

Figure 11. F1 plot for SimpleCNN1D

Figure 11 graphs raw vs. GAN-balanced F1 scores for SimpleCNN1D and indicates improvement in performance after balancing.

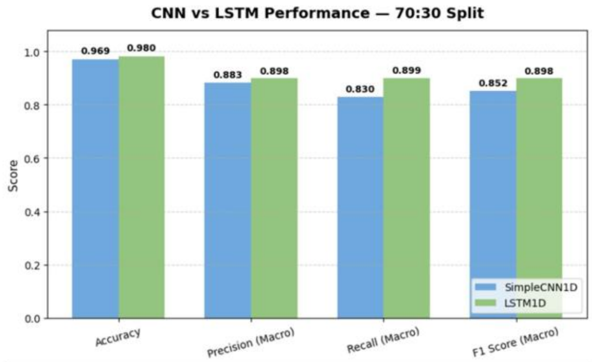

Figure 12 CNN vs LSTM

Figure 12 indicates that in the balanced CNN vs LSTM for 30 Epochs, LSTM1D is better than SimpleCNN1D in all of the splits with the best F1 of 0.898 and Accuracy of 0.980 at the 70:30 split.

Model	Test Accuracy	Precision (Macro)	Recall (Macro)	F1-Score (Macro)
LSTM	0.9796	0.8979	0.8990	0.8983
SimpleCNN	0.9690	0.8833	0.8296	0.8524

Figure 13 Best Model Configurations

Figure 13 shows that LSTM1D is the best model with Macro-F1 score of 0.8983 and accuracy of 0.9796 at epoch 30 (0.7 split, balanced), while SimpleCNN1D achieved F1 score of 0.8524 and accuracy of 0.9690. LSTM1D performed better than SimpleCNN1D.

Algorithm	Split	Mode	Accuracy	F1 Score
LSTM	60:40	Balanced	0.9784	0.8926
LSTM	70:30	Balanced	0.9796	0.8983
LSTM	80:20	Balanced	0.9792	0.8971
SimpleCNN	60:40	Balanced	0.9623	0.8018
SimpleCNN	70:30	Balanced	0.9690	0.8524
SimpleCNN	80:20	Balanced	0.9628	0.8289

Figure 14 CNN vs LSTM comparison table

Figure 14 shows comparison of SimpleCNN1D and LSTM1D models for train splits (0.6, 0.7, 0.8) and epochs (10, 20, 30) with raw vs GAN-balanced results. LSTM1D recorded the best Macro-F1 of 0.8983 and best accuracy of 0.9796 in epoch 30 with 0.7 split (balanced). SimpleCNN1D reported best Macro-F1 0.8524 and best accuracy 0.9690 in epoch 30 with 0.7 split (balanced). Overall, LSTM1D is better than SimpleCNN1D in F1 and accuracy for the majority of setups.

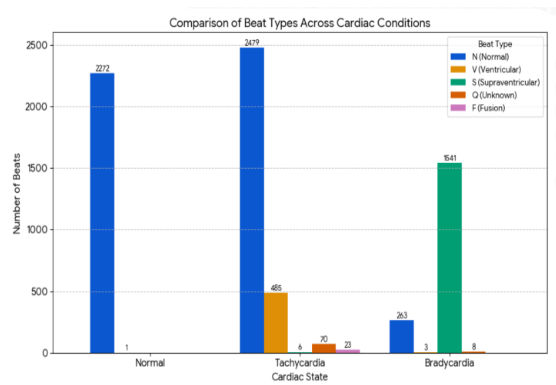

Figure 15 Graph plotted for classification

Figure 15 shows classification of heartbeats (N, V, S, Q, F) distribution was separately analyzed with samples taken from training data set, which comprises cases of heart rate conditions, including bradycardia, normal, and tachycardia, and in all of these tests successful results were received concerning the diagnostic process. Results obtained from these tests have shown that the sample of normal heart rate condition is characterized by high uniformity, as it includes only 2,272 beats, classified as Normal, while the sample of tachycardia condition is highly complex and risky, having 485 beats, classified as Ventricular and 70 beats, classified as Unknown, and the sample of bradycardia has obvious dominance in terms of beats' classifications, as it includes 1,541 beats, classified as Supraventricular.

VII. CONCLUSIONS

The proposed cardiac arrhythmia detection and classification system illustrates the potential of deep learning to improve diagnostic precision for ECG diagnosis. With data augmentation augmented by generative adversarial networks (GANs), the system is capable of handling the class imbalance problems inherent in ECG dataset, MIT-BIH. With CNN, LSTM, and Random Forest models, general feature extraction and classification is leading to accurate identification of heartbeat types like normal, supraventricular, ventricular, fusion, and unknown. Besides, with every classification marked with its clinical implication and recommended cure, the system not only automatically identifies, but also supports clinical decision-making. Therefore, the method enables faster, more uniform, and accurate arrhythmia detection in clinical practice.

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