ECG Signal based Cardiac Arrhythmia Prediction using Hybrid Model Gated Recurrent Unit with Deep Learning based Transformer

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Abstract— **Cardiac Arrhythmia is one of the critical diseases and it is very difficult to diagnose without any specialized cardiologists. ECG signals play an important role in detecting the abnormality in rhythm of heart beats; it means it also helps to identify the normal and abnormal condition of heartbeat. ECG machines and Holter Monitor are dedicated devices used to record and represent heart activity in the form of electrical signals during the treatment of arrhythmia patients. Different conditions of arrhythmia are Bradycardia, Tachycardia and Normal condition of heart, In Bradycardia State heart beats generally slower than Normal condition less than 60 beats per minute but in normal and healthy condition heart beats 60 to 100 times in 60 seconds and in tachycardia condition it just opposite of bradycardia heart beats more than 100 times in 60 seconds. These three different condition of arrhythmias is analyzed through the waves present in cardiac cycle and these waves are represented as P, Q, R, S, T and U wave each wave have its own specific property, count and duration so in this work we have QRS complex which leads the role to identify the number of beats in one minute but mainly our hybrid model works on basis of count of R wave and these waves are extracted from raw ECG signal which recorded from real heart patients. In this research work to predict these different state of arrhythmia in heart patient we have developed a hybrid model a combination of Gated Recurrent Unit and Deep Learning based transformers and we have used four popular datasets and all datasets are freely available on physionet.org and in resultant of our work we found that our model is very lightweight and efficient to process large amount of ECG data and generate the results with better accuracy to predict different state of arrhythmia.**

Index Terms— **Cardiac Arrhythmia Prediction, Deep Learning based Transformers, ECG Signals, Gated Recurrent Unit.**

I. INTRODUCTION

The human Heart is very sensitive and the main part of human body it directly represents the activity, existence of life and reflects the life-threatening results in heart patients. Heart beats should be in normal condition if heart beats are too slow or too fast then this is hilarious and life-threatening for any human being even for healthy humans too because it is not just abnormality in heart beats only it also affects the blood circulation and degrades the oxygen level in blood. It affects brain because lack of sufficient oxygen rich blood in the neural system of the brain overall it affects the whole body because blood flows through the veins in all parts of body so if heart not working in normal condition, it means the heart patient need an ECG or EKG test. In this test an expert cardiologist monitor the activity of heart which generally looks like in the form of zigzag line in the ECG machine or Holter monitor that line in the monitor is the electrical representation of heart activity. ECG machine records the voltage, amplitude and frequency from the human heart, and then it generates the ECG signal in the form of wave.

Traditional manual interpretation of ECG signals takes more time and resources which makes necessary development of automated ECG processing systems [1] and automated detection model using ECG signals could perform better in arrhythmia prediction [2]. Arrhythmia is one of the significant health concerns globally which affect patients with different conditions like morbidity and mortality [4]. Real time arrhythmia classification requires different methods to shrink ECG recording into solid feature sets [6]. ECG signals with low amplitude and noise require advance filtering methods to accurately diagnose the cardiovascular disease [8].

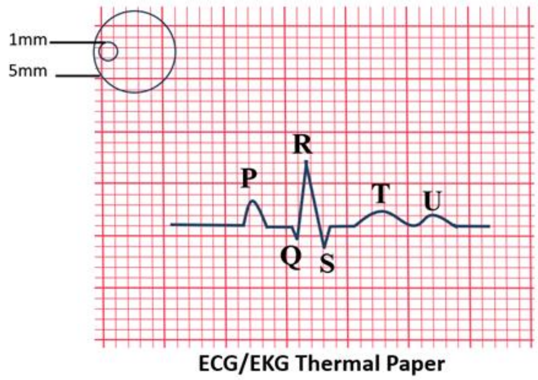

Fig. 1. Cardiac Cycle

In Fig. 1 we can clearly see the waveform of the ECG signal on red-colored with white background EKG paper. EKG paper is the standard paper for printing ECG signals which includes multiple grids and in a grid system there are several boxes. Some of the boxes are large and some of them are small. Large boxes contain 25 small boxes, and the height and width of the small boxes are 1mm and 1mm respectively, and the height of one large box is 5mm and the width is also the same. Each small box represents a duration of 0.04 seconds, and the duration of the large box is 0.20 seconds and the combination of 5 large boxes represents a duration of 1 second. As we know, the ECG signal is the electrical representation of heart activity. In the EKG paper each small box represents the 0.1 (mV) of voltage and each large box represents the 0.5(mV) of voltage. One cardiac cycle consists of P, Q, R, S, T and U waves, each wave joint together by an Isoelectric line and plays an important role in monitoring the activities of the heart.

Role of P, Q, R, S, T and U wave in cardiac cycle:

- **P wave: -** P wave is the first and usually a positive wave in ECG signal and it represents the atrial depolarization.
- **Q wave: -** Q wave is the second wave in ECG signal, but it is considered as first wave in QRS complex. It is a negative wave in nature and occurs by depolarization of interventricular septum.
- **R wave: -** R wave is one of the most positive wave than other waves and leads an important role in identifying the pattern of heartbeat. It occurs due to depolarization of the ventricular.
- **S wave: -** S wave is the final wave of QRS complex, and it represents the final depolarization of ventricular.
- **T wave: -** T wave is a slightly positive wave, and it represents ventricular repolarization.
- **U wave: -** U wave is also a positive wave, and it represents the repolarization of ventricular myocardium.

In this research work our hybrid model works based on QRS complex, mainly the occurrences of R wave and the timing. We have used four popular datasets which are freely available on physionet.org[14] which are listed as CU Ventricular Tachyarrhythmia Database [15], ECG-ID Database [16], PTB-XL [17] and MIT-BIH Arrhythmia Database [19]. These datasets are trusted and used in most of the research work. In the literature review section we did a comparative analysis based on multiple research papers where we found some similarities and some unique differences in reference of my hybrid model. Deep learning-based transfers and gated recurrent unit have been separately used for different research problems, and we deployed it on ECG signals and found that it gives better performance and results including accuracy, recall, precision, and f1 score.

II. LITERATURE REVIEW

In most of the research work, authors have used machine learning traditional approach to process ECG signals and predict arrhythmia but in recent years deep learning is adopted for this purpose and the result from the deep learning models performs better than machine learning models for the classification and prediction purposes.

In Table I. I did a detailed comparative analysis of multiple research papers and found that the performance of our hybrid model GRU- Deep Learning-based Transformers gives better results.

Table I: Comparative analysis for literature review based on performance.

Author s	Paper Title	Database used	Classifier	Accura cy/

				performance
[1] Liang-Hung Wang et al.	Three-Heartbeat Multilead ECG Recognition Method for Arrhythmia Classification	MIT-BIH Arrhythmia Database	1D-CNN with Priority Model Integrated Voting	94.4%
[2] Chen et al.	A deep learning model for the classification of atrial fibrillation in critically ill patients	Chapman 12-lead ECG, KHSC ICU Telemetry	Deep Convolutional Neural Network (4-lead adapted)	Sensitivity: 84%, Specificity: 89%, PPV: 55%, NPV: 97%
[3] Xinwu Yang et al.	Categorization of ECG signals based on the dense recurrent network	PhysioNet/ CinC 2017 Challenge	DRNet (DenseNet + BiLSTM) + MFL	Accuracy (Avg F1) 0.852
[4] Zakaria et al.	Morphological Arrhythmia Classification Based on Inter-Patient and Two Leads ECG Using Machine Learning	MIT-BIH Arrhythmia Database	KNN, SVM, Random Forest, Ensemble Learning	87%
[5] Tahseen Ullah et al.	Machine Learning-Based Cardiovascular Disease Detection Using Optimal Feature Selection	Hungarian Heart Disease (small), Kaggle (large)	Extra Tree, Random Forest with PSO optimization	100% (small), 78% (large)
[6] Saeed et al.	ECG Classification With Event-Driven Sampling	MIT-BIH Arrhythmia & Supraventricular Arrhythmia	Three-layered ANN with SMOTE	F1-scores: N (0.99), S (0.90), V (0.93), F (0.76).
[7] Zubair et al.	Deep Representation Learning With Sample Generation and Augmented Attention Module for Imbalanced ECG Classification	MIT-BIH Arrhythmia	1D-CNN + Augmented Attention Module	96.19%
[8] Ahlam Fadhil Mahmood et al.	RLS adaptive filter co-design for de-noising ECG signal	MIT-BIH Arrhythmia Database	Co-designed RLS Filter (FPGA + Microblaze)	89.78% SNR improvement, 56.2% power reduction

[9] Laura Falaschetti et al.	ECG-Based Arrhythmia Classification using Recurrent Neural Networks in Embedded Systems	MIT-BIH Arrhythmia Database	RNN, GRU, LSTM, BiLSTM	~90% (LSTM)
[10] Tang et al.	Optimizing machine learning for enhanced automated ECG analysis in cardiovascular healthcare	PTB Diagnostic ECG Database	XGBoost + JADE (Optimized)	86%
[11] Farrokhi et al.	Reliable Peak Detection and Feature Extraction for Wireless ECGs	Shimmer platform + MIT-BIH	Adaptive thresholding, Wavelet Transform	R: 95%, T: 87%, P: 84%
[12] Reznichenko et al.	Comparing ECG Lead Subsets for Heart Arrhythmia/ECG Pattern Classification: Convolutional Neural Networks and Random Forest	PhysioNet 2020	CNN, RF	0.761 (DL), 0.759 (CML)
[13] Lai et al.	Optimal ECG-Lead Selection for Deep Learning on Abnormality Classification	CPSC 2018 (8 ECG abnormality types)	CNN	F1-Score: ~0.802
Proposed Method	ECG Signal based Cardiac Arrhythmia Prediction using Hybrid Model Gated Recurrent Unit with Deep Learning based Transformer	MIT-BIH Arrhythmia Database, ECG-ID Database, CU Ventricular Tachyarrhythmia Database and PTB-XL.	Deep learning-based Transformers with Gated Recurrent Unit	97.080 %

Existing methods for ECG classification are dealing with challenges like incomplete waveform and data imbalance [1] and deep learning-based model have power to learn directly from the raw data [2]. Advancement in machine learning is also found to be better in this field, but it is lacking in selecting optimal features from high-dimensional datasets [5] while deep learning performs better in processing high-dimensional ECG Data [12]. In ECG Signals analysis attention mechanisms techniques dynamically weighting the features based on importance but it is underexplored for RR intervals [7]. Now a day numerus machine learning and deep learning-based research work has focused on classifying ECG signals and in most of the research work, researchers explore different techniques such as optimization, feature extraction and transfer learning to address the challenges to categorize the Heartbeats [10] but tackling the overfitting problem in deep learning-based models is found challenging [13].

III. RESEARCH METHODOLOGY

In this research work we have used a hybrid approach to predict arrhythmia using Gated Recurrent Unit (GRU) and Transformers. The aim is to develop and provide a robust and efficient system for diagnosing and predicting cardiovascular conditions of the heart. This research methodology is structured in different phases: data collection, data pre-processing, feature extraction, model design, training, testing and evaluation and at last deployment of the trained and working model into a real user-friendly application.

A. Data Collection:

- **MIT-BIH Arrhythmia Database: -** This database is used in multiple research work and recording of ECG signals is obtained from 47 subjects and the duration of ECG recording is 30 minutes and recorded with the support of Beth Israel Deaconess Medical Center and MIT.
- **CU Ventricular Tachyarrhythmia Database: -** This dataset contains 35 ECG recordings of heart patients recorded using long-term ECG Holter machine and the duration of recording is 8 minute.
- **ECG-ID Database: -** It contains 310 ECG recordings and each recording recorded for 20 seconds.
- **PTB-XL, a large publicly available electrocardiography dataset: -** This is one of the largest dataset for ECG signals and it contains 12-lead ECGs from 18869 heart patients of 10 second ECG recording length.

From these four datasets I have randomly selected ECG recordings where the total number of recordings are 2051 in which 855 ECG recording belongs to Bradycardia, 843 belongs to Normal category and 353 recording belongs to Tachycardia condition.

B. Data Pre-processing:

Datasets used for this research have similar type of ECG recordings and each ECG recordings processed through the following steps: -

- **Signal Extraction:** The raw ECG signals are extracted and read using the numpy and biosppy library by converting binary data into numerical amplitude values. Each record is normalized to improve model performance and interpretability by scaling values to the range of [0, 1].
- **Filtering:** We used Biosppy library for digital filtering which cleans the signal by removing additional noise and irrelevant artifacts, which is mandatory for accurate feature extraction.
- **Peak Detection:** R-peaks are detected from the filtered signals using biosppy library, facilitating the monitoring of heart activity and enabling the calculation of the heart rate.
- **Segmentation:** Each ECG signal is segmented into manageable epochs based on user-determined durations, which prepares the data for analysis and ensures that the model receives consistent input sizes.

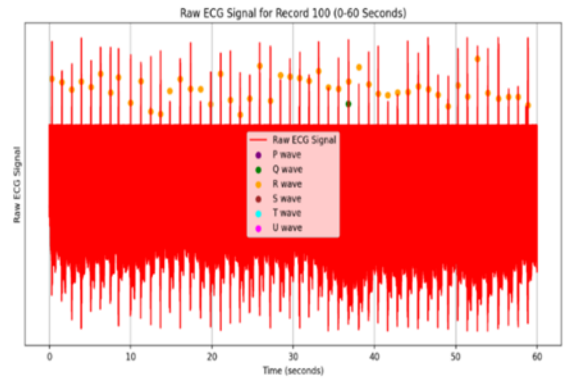

Fig. 2. Raw ECG Signals

In Fig. 2 we clearly see how much noise in the raw ECG signals and the P, Q, R, S, T and U waves overlap together and we cannot identify the difference between these waves.

C. Feature Extraction:

We extracted two important features for this research work as follows:

- Total Number of R-peaks: This feature indicates the number of heartbeats within the selected minimum duration and maximum duration, and it gives the variation in heartbeat.
- Heart Rate (BPM): We have used the formula to count the heartbeat per minute formula given as follows:

$$bpm = np.round(rpeak_{count}/(\max\_duration - \min\_duration)/60))$$

Where:

- bpm = beats per minute.
- rpeak_count = number of r waves or peaks in ECG signal.
- max_duration = maximum duration is selected by user.
- min_duration = minimum duration is selected by user.

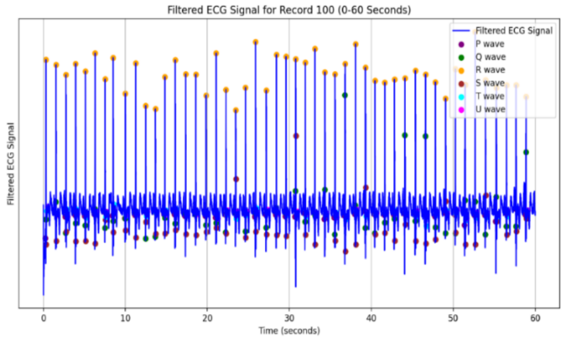

Fig. 3. Filtered ECG Signals

In Fig. 3 we removed the noise from raw ECG signals using biosppy library and now each wave is differentiated with each other and clearly visible the instance of each wave.

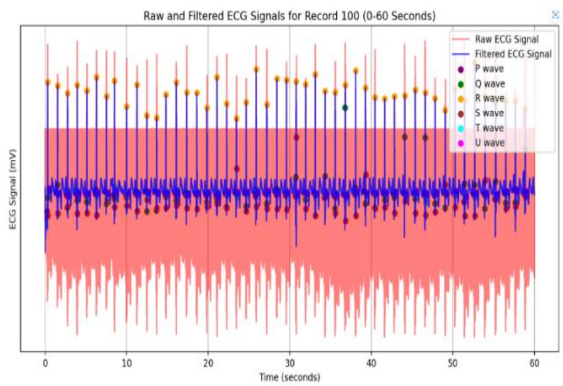

Fig. 4. Raw and Filtered ECG Signals

In Fig. 4 this represents the combination of raw ECG signals and filtered ECG signals, and for the processing of ECG signals we have used Biosppy python library[18] which handles the ECG biological signals efficiently and accurately.

D. Data Augmentation and Handling Imbalance:

The Synthetic Minority Over-sampling Technique (SMOTE) is implemented to balance the imbalance in arrhythmia classifications, when specific types of arrhythmia data is not sufficient. SMOTE produces synthetic data for minority class and stabilizes training processes, helping the model learn effectively across all classes.

E. Model Design and Architecture:

Pictorial representation of Hybrid GRU-Transformer Model for Arrhythmia Prediction based on ECG signal as follows:

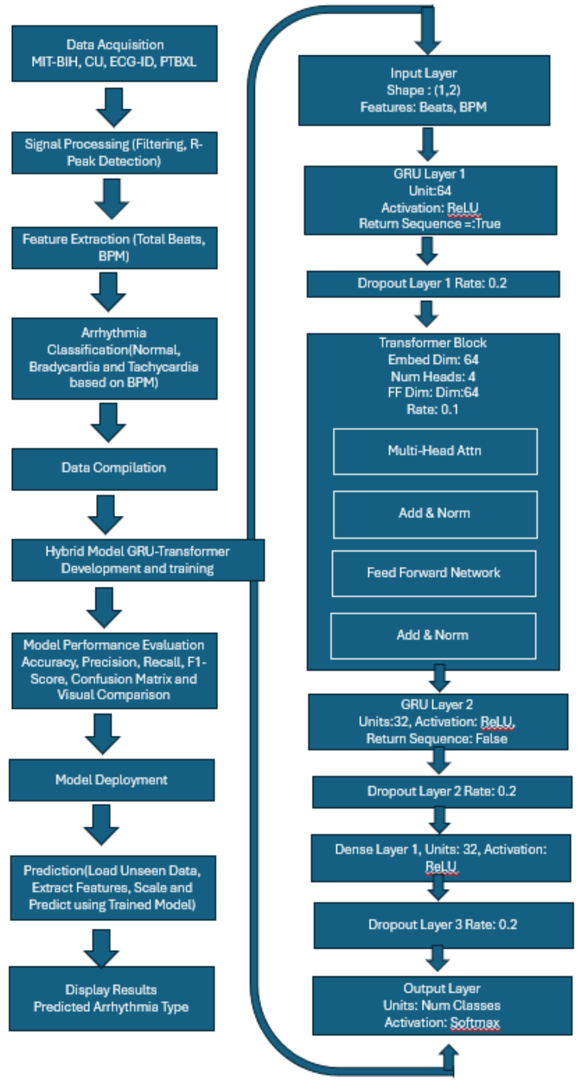

Fig. 5. Hybrid Model Design

In Fig. 5 the hybrid model, a combination of GRU layers and Transformer blocks, is designed to learn both long-term and short-term dependencies in ECG based sequential data.

F. Gated Recurrent Units (GRU):

The first GRU layer is utilized to derive temporal dependencies within the ECG features. GRUs are chosen over traditional RNNs due to their efficiency and ability to capture dependencies without suffering from vanishing gradient issues. GRUs uses gates to control the process flow of information within the network. These gates decide what information to keep from the previous step and what the new information to pass to the current input. Gates are as follows:

- **Update Gate (Z_t):** It controls how much the data from previous hidden state (ht-1) is carried over to the current hidden state.
- **Reset Gate (r_t):** It controls how much the data from previous hidden state is ignored.
- **Candidate Hidden State ($\tilde{h}_t$):** New hidden state calculated based on current processing input state and the reset hidden state.
- **Hidden State (h_t):** This is considered as last hidden state at the current processing time step, which is a combination of previous hidden state and candidate hidden state, and it is managed by update gate.

Formulas are as follows:

- **Update Gate:** $Z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z)$
- **Reset Gate:** $r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r)$
- **Candidate Hidden State:** $\tilde{h}_t = tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h)$
- **Hidden State:** $h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t$

Where:
h_{t-1} it represents hidden state at the previous step.
W_z, W_r, W_h are weight matrices for the input.
U_z, U_r, U_h are weight matrices for the recurrent connections.
b_z, b_r, b_h are bias vectors.
σ is the sigmoid activation function which gives output values 0 and 1.
tanh is the hyperbolic tangent activation function, which gives output values between -1 and 1.
⊙ it represents the element- wise product (Hadamard product)

In our model the first GRU layer process input features like heartbeat counts and Beats per minute to learn temporal patterns from ECG data which is associated with different arrythmias and process it. The first GRU layer, with 64 units, captures short-term dependencies, while the second with 32 units further refines this representation after the Transformer block. Relu activation is used for non-linear feature extraction, and the Dropout layers serve as regularization function to prevent overfitting. During the training dropout applied after the GRU layers to control the overfitting by randomly setting a fraction of the input units to zero during training.

G. Transformer Block:

Transformer Block Following the GRU layer, a Transformer block is used to capture long-range dependencies and contextual connections in data in the sequential data using attention mechanisms. The Multi-Head Self-Attention mechanism grants control to model to weigh the effect of different time steps more efficaciously than GRUs alone.

Workflow of Transformer:

- **Self-Attention:** It is the mechanism which grants control permission to the model to analyze the effective value of the distinct parts of the input values sequence during the processing of each element. For each element, it calculates attention scores with all other elements in the sequence.
- **Multi-Head:** It performs attention mechanism repeatedly in parallel with different learned linear arrangement of the input. The results from these "heads" are then grouped and linearly transformed. This permits the model to attend to different scenarios of data simultaneously.
- **Feed-Forward Network:** After the attention mechanism, the output is passed through a simple feed-forward deep learning based neural network.
- **Add & Normalize:** Adding the input to the output of the sub-layer and layer normalization is applied after the attention and feed-forward layers to improve training stability and performance.

Formulas for understanding the Multi-Head Attention as follows:

Query, Key, Value: Query, Key and Value are denoted as Q, K, V respectively, are the vectors in which the input is linearly transformed for each element in the sequence.

$$Q = XW_Q$$

$$K = XW_k$$

$$V = XW_v$$

Where is the input sequence and W_Q, W_k, W_v are learned weight matrices.

- **Scaled Dot-Product Attention:** This is the important calculation of attention mechanism for a single head.

$$Attention(Q,K,V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where d_k is the dimension of the important vectors which are incorporated for scaling to control and prevent the dot products from becoming too large.

- **Multi-Head Attention:** The outputs of multiple attention heads are concatenated and linearly transformed.

$$Multihead = Concat(head_1, \ldots\ldots, head_h)W^o$$

Where headi = Attention (QWq(i), KWk(i), VWv(i)) for the ith head and Wo is a learned output weight matrix.

- **Dense Layers:** These are the fully connected layers and used for classification.

In a dense layer all the neurons relate to each other in the previous layer, and it performs a linear transformation followed by an activation function.

Formula for dense layer as follows:

$$y = f(W_x + b)$$

Where input vector is denoted as x, weight matrix denoted as W, bias vector is denoted as b and f is the activation function i.e. ReLU in the hidden layers, softmax in the output layer.

H. Input Layer and Model Training:

The model is developed to accept input sequences shaped as (batch_size, time_steps, features), which is set up during data preprocessing by reshaping the training and test datasets.

Adam optimizer is used for its adaptive learning rate and enhancing convergence speed. The loss function is based on sparse categorical cross-entropy and applicable for multi-class classification problems. Early stopping is implemented to prevent and control the overfitting and monitored using validation loss.

The training and evaluation process is divided into several epochs:

- **Epochs:** This model is trained for a maximum of 100 epochs. The training dataset is divided into training sets and validation sets for monitoring performance.
- **Batch Size:** A batch size of 16 is used, balancing the computational efficiency and the stability of the model updates.
- **Overfitting Prevention:** Regularization techniques, including dropout layers, are employed throughout the training process to mitigate overfitting, ensuring that the model generalizes effectively to the new unseen data.

I. Model Evaluation:

After the completion of training the performance of the model is evaluated using the test dataset which is separated out initially. Evaluation metrics include Accuracy, Recall, Precision and F1-Score.

The metrics provide a detailed overview of performance and are reported alongside the confusion matrix, which visualizes the performance across different classes.

IV. RESULTS

In this section we have discussed in detail the result evaluation process in reference to our hybrid GRU-Transformer Model. Our model performance is up to the mark in classifying different types of arrhythmias (Normal, Bradycardia, Tachycardia) based on ECG signal. The analysis of the results is represented in the form of visual matrix and graphs.

A. Confusion Matrix:

Confusion matrix represents the model's performance for classification based on test data in the form of table.

In each class how many instances were correctly classified and how many instances were incorrectly classified, and in which classes instances were confused.

We have measured the performance of our model based on several important metrics as follows:

B. Accuracy

This is the most straightforward metric defines the ratio of accurately classified entries that is true positives entries and true negatives entries out of the total the total number of entries. While just simple accuracy can mislead in case of imbalance in datasets where the ratio of entries is not balanced in different classes.

Formula to calculate accuracy we have used:

$$Accuracy(\%) = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100$$

C. Precision

Precision measures the accuracy of only positive predictions that are truly correct. It shows the ratio of the number of true positive predictions out of total predicted positive.

$$Precision(\%) = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100$$

D. Recall

Recall is also known as sensitivity, and it represents the ratio of actual positives which were correctly predicted by the model.

$$Recall(\%) = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100$$

E. F1 Score

F1-score calculates the reciprocal mean of precision and recall. It balances both precision and recall. It is required for uneven class distribution where the dataset is imbalanced.

$$F1 - Score(\%) = \frac{2 \times \text{TP}}{2 \times \text{TP} + \text{FP} + \text{FN}} \times 100$$

Where:

TP (True Positive): It shows the number of correctly predicted entries in Positive class.

TN (True Negative): It shows the number of correctly predicted entries in Negative class.

FP (False Positive): It shows the number of incorrectly predicted entries in Positive class.

FN (False Negative): It shows the number of incorrectly predicted entries in negative class.

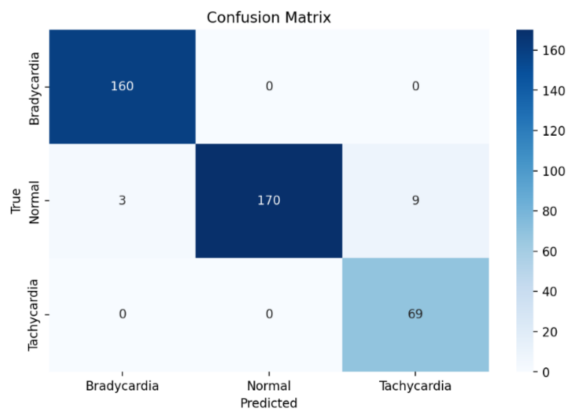

Fig. 6. Confusion Matrix for Arrhythmia

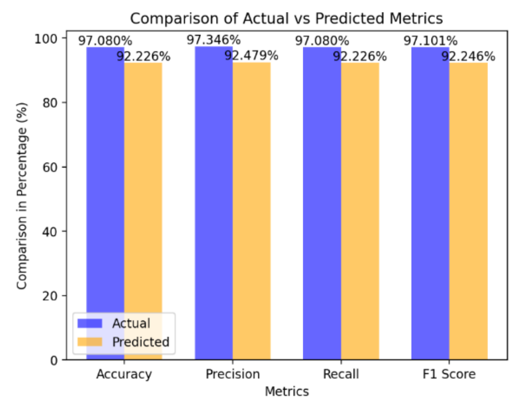

Fig. 7. Comparison of Actual Vs Predicted

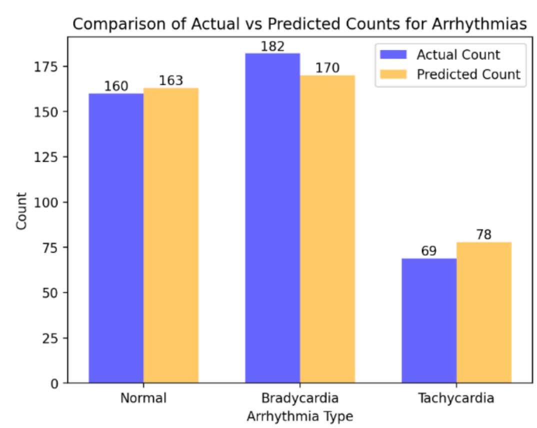

Fig. 8. Comparison for Arrhythmia Type

In Fig. 6 the confusion matrix is generated by using GRU – Transformer based hybrid model and in Fig. 7 we can see the comparison between actual and predicted for accuracy, recall, precision and f1-score and in the last Fig. 8 it shows the total counts of actual patients and predicted patients.

As the result of this research work, we achieved the accuracy of 97.080%, precision of 97.346%, recall of 97.080% and f1-score of 97.101%.

IV. CONCLUSION

In conclusion, in this research work we developed a hybrid model, a combination of gated recurrent unit and deep learning base transformer blocks. This hybrid model is very efficient and lightweight in processing the raw ECG recording data and to predict cardiac arrhythmia from ECG signals. The main features in this research work are used as the total number of beats and beats per minute because cardiac arrhythmia diseases are the irregularities in the heartbeats, so these are the main features which play an important role in generating the input for the hybrid model. This project is not only limited to predicting cardiac arrhythmia disease, but it can also even be used to read the raw ECG signals from most of the data sources. We have calculated the number of beats based on R peaks. In one cardiac cycle, there are mainly six waves which are denoted as P, Q, R, S, T and U, where the combination of Q, R and S waves makes the QRS complex and in QRS complex, the R wave is the main wave to count the number of heartbeats at any duration, and it also helps to calculate the Total number of heart beats. We found that the Biosppy library is one of the most powerful python libraries to read and remove the noise and artifacts from the ECG biological signals and, more importantly, it enables the localization of R-Peaks so that it makes it easy to count the beats per minute. The hybrid GRU- Transformer model in this work represents a refined approach to arrhythmia prediction. The GRU layer powers the ability to process the sequential data from the extracted features and capture local temporal patterns. Transformer blocks add the advancement in GRU with its self-attention technique to capture the relationships and long-range dependencies between distinct segments of feature sequence. This unique combination aims to provide a more detailed understanding of heartbeat rhythm and lead to improving the overall performance along with the different performance matrix of the model.

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