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Hybrid Deep Learning algorithm for Abnormal Heart Beat detection using ECG Signals

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ABSTRACT

According to the World Health Organization (WHO), heart disease is increasing worldwide due to various factors such as lifestyle, food habits, and lack of physical activity. Recently, even adults and children have been affected by heart disease. The abnormal heartbeat analysis and classification are crucial for proper treatment. The electrocardiogram (ECG) is globally used for analyzing heart function. However, the manual inspection of ECG signals is very difficult and time-consuming. Many research works focus on ECG signal analysis to detect and classify abnormal heartbeats. ECG signals are unstable and vary from person to person based on age and other factors, making effective feature extraction challenging. Moreover, achieving the required accuracy remains a challenge. To address this issue, a novel hybrid Deep Learning (DL) model called Transformer with Multihead Attention (MHA)-Bidirectional Long Short Term Memory (BiLSTM) is proposed. The Transformer captures long-range dependencies, while the BiLSTM extracts sequential dependencies from the ECG signal. The integration of these two models not only extracts important features but also maintains the temporal structure, leading to improved classification accuracy. The proposed DL model is compared with traditional standalone models such as Transformer, BiLSTM, and Convolutional Neural Network (CNN). For evaluation, the MIT-BIH dataset is used, which consists of normal and four types of abnormal heartbeats. The experimental results show that the proposed network effectively classifies abnormal heartbeats with an accuracy of 98.93%. In comparison, the Transformer model achieves 96.27%, CNN 93.73%, and BiLSTM 95.47%. Additionally, the proposed network is compared with recent research works. From the comparison and evaluation, it is evident that the proposed network is suitable for highly reliable abnormal heartbeat detection. This can be helpful for doctors in detecting cardiac diseases in minimal time.

Keywords: Heart Beat, Electrocardiogram, Augmentation, Transformer, Bidirectional Long Short Term Memory, Confusion Matrix, Performance Measure.

I. INTRODUCTION

ECG records cardiac electrical activity and is useful for detecting abnormalities in the heartbeat [1]. Although ECGs are imperfect and cannot always detect all disorders, they provide valuable information regarding heart health. It is most commonly used to diagnose coronary artery disease, arrhythmias, myocardial infarction, and cardiomyopathy because an ECG is a simple and non-invasive way to detect these issues [2]. This non-invasive method causes no injury or discomfort to patients and can be performed multiple times, allowing for continuous monitoring over long periods. Furthermore, ECG equipment, such as Holter monitors, is inexpensive and commonly used in medical settings, ensuring widespread availability [3]. These devices provide quick and extensive heart data, such as rhythm,

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rate, and signs of potential illnesses. Established ECG interpretation guidelines help identify specific indicators for different types of cardiac disorder.

Despite the importance of ECGs in abnormal heartbeat detection and categorization, several challenges must be overcome when evaluating them. A normal ECG investigation is labor-intensive and relies on the experience of trained clinicians, which might lead to interpretation errors [4]. Another significant shortcoming of conventional ECG equipment is that it may miss transient or intermittent arrhythmias that do not occur while the machine is recording. The placement and demand for electrodes may also impact the reliability of the recordings, causing patients discomfort for extended periods. Furthermore, ECG signals are susceptible to noise and artifacts [5]. Complex signal processing techniques are required to interpret noise contamination accurately [6].

This provides the framework for designing and implementing automated, low-cost solutions based on DL and Machine Learning (ML) models. Such technologies allow for continuous tracking and more precise analysis of ECG readings, enhancing the possibility of detecting abnormal heartbeats. The application of ML and DL networks in ECG analysis may also standardize interpretations, minimizing errors in human analysis and improving patient health.

Many ML and DL methods have been published in the literature for categorizing ECG data as normal or abnormal. Some of the notable works on ECG signals are selected and presented in Table I. The table provides complete information about the research, including the models used, data employed for validating the models, and the advantages and limitations of each study. This helps identify research gaps and develop a novel hybrid DL model for abnormal heartbeat detection.

TABLE I. RESEARCH WORKS ON ECG SIGNAL CLASSIFICATION

Ref	**Model Used**	**Data Used**	**Advantage**	**Limitation**
[7]	Marine Predators Optimized Random Forest	MIT-BIH, St. Petersburg Institute of Cardiological Techniques (INCART)	Improved classification accuracy using marine predator optimization. Suitable for IoT-assisted smart healthcare.	Performance depends on feature extraction quality. DL models could further enhance performance.
[8]	Cubic SVM	Baqiyatallah, PTB Diagnostic	High accuracy in classifying 15-lead ECG heartbeats. Fast and easy to implement. Outperforms previous methods by effective feature extraction using a Histogram of Oriented Gradients.	Not fully automatic, and requires a cardiologist to extract heartbeats.
[9]	CNN-SVM	Physionet	No manual feature extraction is required. Outperforms AlexNet and SqueezeNet in ECG classification.	Requires more computational resources due to deep CNN. The feature extraction process is complex.
[10]	CNN-kNN	MIT-BIH, PTB Diagnostics	No need for handcrafted feature extraction. Outperforms 1D-CNN and other state-of-the-art models.	The computational cost of CNN-based feature extraction is high
[11]	Encoder-Decoder model with ResNet + KNN	PTB XL PTB diagnostic	Combines metric learning with ResNet for better feature extraction. Incorporates RR interval temporal features for enhanced classification	Requires manual extraction of RR interval features, increasing training time. Does not optimize inter-class distance, affecting classification efficiency.

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[12]	Dual ConvNet-Attention	MIT-BIH	Cost-sensitive approach improves class imbalance handling. Dual CNN with attention enhances feature extraction.	Needs further comparison with other cost-sensitive techniques. Requires hyperparameter tuning using methods to minimize misclassification
[13]	Fine-tuned ResNet by Short-Term Fourier Transform	MIT-BIH	Converts 1D ECG signals into 2D spectrograms for better feature extraction. Highlights importance of proper dataset splitting to prevent data leakage	Inconsistent use of MIT-BIH dataset across studies affects comparison.
[14]	1D-CNN	MIT-BIH	Fast and automatic classification of cardiac arrhythmias. Uses noise-attenuated ECG signals to improve accuracy	Imbalanced dataset affects model generalization despite class-weight adjustment.
[15]	Siamese CNN	INCART	Effective for classifying heartbeats with limited data. Works well for rare cardiovascular diseases where data is scarce	Computational cost is higher when using MSE and RMSE loss functions. Needs fine-tuning for better decision-making and parameter optimization
[16]	Heart beat dynamics and KNN	MIT-BIH	Novel heartbeat dynamics feature enhances classification sensitivity. Works well with classical ML models, reducing computational cost compared to DL models. Insensitive to dataset imbalance	Lacks DL feature fusion, which could improve performance
[17]	Chi-square Classifier with Particle Swarm Optimization	MIT-BIH	PSO enhances feature selection, and results in outperforming traditional ML and DL techniques.	Dependence on Chi-square distance may limit adaptability to highly variable ECG signals
[18]	CNN with frequency channel attention (FCA)	MIT-BIH	Utilizes multimodal image fusion for enhanced ECG classification. Integrates FCA to improve feature weighting and accuracy.	High computational complexity due to transformation of 1D signals into images. Significant increase in memory usage and computational cost.

From the literature survey, several points have been noted. The model requires further improvement to achieve better accuracy. Although some models attain high accuracy, they are computationally expensive. To address these limitations, a novel hybrid DL model, Transformer with MHA-BiLSTM, is proposed. This model effectively extracts all important features of the signal, leading to higher accuracy. The contributions of this research are detailed below.

- The Transformer with MHA-BiLSTM is proposed. The Transformer encoder with MHA extracts long-range dependencies from the ECG signal by focusing on important heartbeat patterns, while BiLSTM further identifies the most significant features by maintaining the temporal pattern.
- The ECG data is collected from the MIT-BIH database and undergoes necessary pre-processing steps, including denoising and data balancing, to ensure a clean and balanced signal.
- The proposed model is compared with standalone networks to analyze performance using both positive and negative evaluation metrics. Additionally, it is compared with existing research works.

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II. MATERIALS AND METHODS

The research methodology uses a hybrid DL network for abnormal heartbeat classification using ECG signals. The proposed methodology has four stages. First, the data is collected from a trustworthy site or database. Second, the raw ECG data undergoes several processing steps, including interpolation, denoising, and balancing. Third, the proposed network is designed. Finally, to evaluate the proposed network, the model is compared with standalone models and existing research works. The workflow of the proposed methodology is shown in Figure 1.

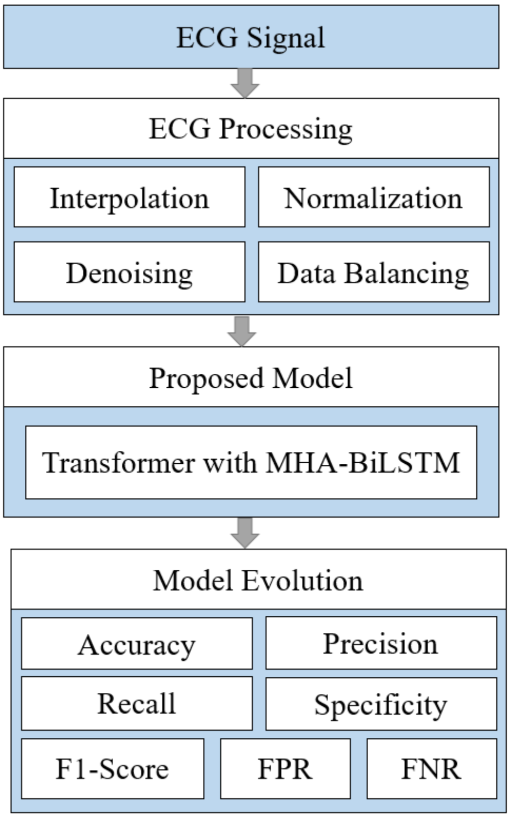

Fig. 1. Proposed Methodology work flow

A. *Data Acquisition*

In this research, the MIT-BIH dataset is used. The PhysioNet portal [19] provides free online access to the MIT-BIH Arrhythmia Database [20]. The database consists of 48 half-hour segments of 2-channel ambulatory ECG readings from 47 different participants. The data was digitized using a sample rate of 360 Hz and an 11-bit resolution across a 10 mV range. Table II shows the data distribution of the MIT-BIH database, presenting the proportion of each category. The dataset is extremely unbalanced: approximately 82.77% belong to the normal (N) class, 0.73% to the fusion of ventricular and normal beats (F), 6.61% to premature ventricular contractions (V), 2.54% to supraventricular premature or ectopic beats (S), and 7.35% to paced or unknown beats (Q).

TABLE II. MIT-BIH DATA DISTRIBUTION

Class	Proportion (%)	Samples	Balanced Data
N	82.77	90,589	1500
S	2.54	2779	1500
V	6.61	7236	1500
F	0.73	803	1500
Q	7.35	8039	1500
Total	100.00	109,446	7500

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B. Data Processing

Pre-processing must be part of the ECG categorization mechanism. The signals may contain noise and have different amplitudes and sampling rates. These ECG signals undergo pre-processing to ensure that the data is consistent, clean, and appropriate for training the proposed models. The ECG dataset went through the following pre-processing steps:

Interpolation

The digitized values varied in length due to small differences in the diameters of the selected locations and the various types of heartbeats. Linear interpolation [21] was used to generate feature vectors from all digital signals of equal length. The linear interpolation formula is given in Equation (1)

$$y = y_1 + \frac{(x-x_1).(y_2-y_1)}{x_2-x_1} \quad [1]$$

The digitized heartbeat signals were interpolated to a length of 234 after the segmented heartbeats' feature length. This resulted in a feature vector of equal length for each digital heartbeat.

Noise Removal

The raw signals are aggregated with noise, including power frequency, electromyography, and other interferences. To detect abnormal heartbeats accurately, the signal must be free from interference. To achieve this, the signals were denoised using the Discrete Wavelet Transform [22] before being fed into the model. This helps eliminate distortion in the QRS signal, making it simpler to detect RR intervals.

Normalization

The amplitude of the signal can change randomly. To allow the model to correctly learn the properties, the heartbeats needed to be scaled to a standard scale. Standard scaling or normalization between 0 and 1 can be used for this. The normalization formula is given in Equation (2):

$$x_{normalized} = \frac{x-x_{min}}{x_{max}-x_{min}} \quad [2]$$

where x_{min} and x_{max} represents the minimum and maximum value.

Data Balancing

The model may be biased toward the dominant class due to class imbalance, resulting in poor or unsatisfactory classification of the minority class. This has a major impact on numerous performance parameters, including classification accuracy [23]. Another issue with the dataset is the lack of balance between instances and target classes. It is clear that the total occurrences in the N class far outnumber those in the F class, with 90,589 samples in the N class and 803 cases in the F class. Thus, the proposed technique supports the Synthetic Minority Oversampling Technique (SMOTE) [24]. The minority classes are constructed using SMOTE, which also downsamples the majority classes. The majority classes (N, S, V, and Q) were downsampled to 1,500 instances each, while the minority class (F) was upsampled in this study, resulting in a 25% distribution of the total data. The even and biased distribution of classes and resampling preserved the data's integrity while reducing the burden on neural networks.

C. Proposed Model

The Transformer with MHA-BiLSTM is proposed in this research. First, the Transformer extracts long-range dependencies from the ECG signal during the encoding phase. In the decoding phase, the BiLSTM and fully connected layer are integrated to refine the most important features while maintaining the temporal sequence. The working of the Transformer and BiLSTM is discussed in detail below.

Transformer

The Transformer has recently emerged as a key paradigm for sequence-to-sequence problems and natural language processing [25]. The Transformer uses self-attention mechanisms to successfully capture long-range correlations in input sequences and the structure of the transformer module is shown in Figure 2. The Transformer has a

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parallelizable architecture, which allows for faster training on parallel hardware, as opposed to traditional convolutional or recurrent structures, which rely on sequential processing.

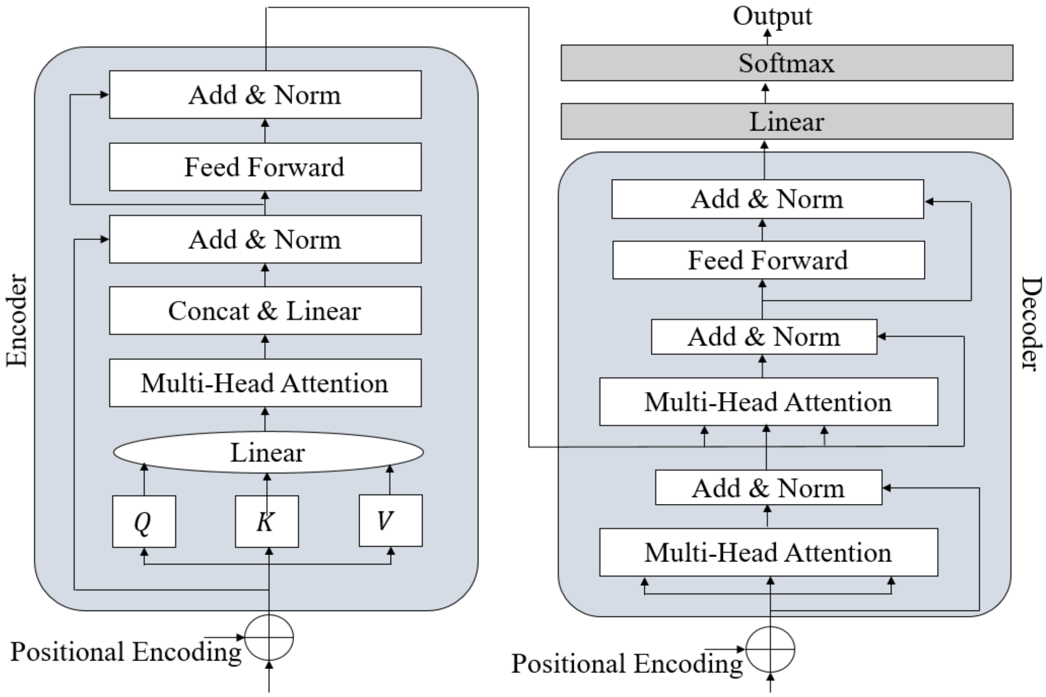

Fig. 2. Architecture of Transformer Model

The self-attention mechanism generates attention weights for an input sequence, $X = \{x_1, x_2, \dots, x_n\}$, so that each element in the series can attend to every other element. This is performed using the expression in Equation (3):

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad [3]$$

In this scenario, d_k denotes the key vector's dimension, whereas Q, K, and V denote the query, key, and value matrices, respectively. The weight that each component contributes to the final result is calculated by normalizing the attention scores using the SoftMax approach. The Transformer employs a technique known as MHA to improve the expressive power of self-attention [26]. The input sequences are linearly projected into multiple subspaces, each utilizing a distinct attention mechanism. The outputs from these attention heads are then concatenated and undergo a linear transformation to generate the final result. The MHA is defined in Equation (4):

$$MultiHead(Q, K, V) = Concat(head^1, head^2, \dots, head^h)W_o \quad [4]$$

Where $head^i = Attention\left(QW_Q^i, KW_K^i, VW_V^i\right)$ and weight matrices W_Q^i, W_K^i, W_V^i, and W_o are all learnable. This multi-head technique, which captures a range of patterns and relationships, allows the model to focus on multiple components of the input sequence simultaneously. The Transformer includes a feed-forward layer that captures complex, non-linear interactions within encoded representations, thereby enhancing the self-attention process [27]. A feed-forward neural network, consisting of two linear transformations with a ReLU function, processes each point in the sequence separately:

$$FFN(x) = ReLU(xW_1 + b_1)W_2 + b_2 \quad [5]$$

The learnable parameters in this scenario are W_1, b_1, W_2, and b_2. By increasing flexibility, the feed-forward layer enhances the network's capacity to learn complex representations by recognizing intricate patterns and relationships in data. Finally, the prediction loss L_{pred} is determined to minimize the difference between the predicted class $(\hat{y})$ and the actual class (y), as illustrated in Equation (6):

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$$L_{pred} = \frac{1}{N}\sum_{i=1}^{N} \quad \|y_i - \hat{y}_i\|_2 \qquad [6]$$

Where, N represents the number of sample sequences in our dataset.

BiLSTM

The LSTM [28] is an improved RNN that tackles the issue of long-distance information loss in extended sequences. Gradient explosion and vanishing issues in an RNN structure are addressed, and temporal data is processed [29]. It can reduce unnecessary memory usage while retaining crucial information. LSTM manages information exchange and storage during forward propagation using the forget gate, input gate, and output gate, which are the three gate structures of the hidden layer memory cell. Equation (7) contains the formula for computing each of the parameters:

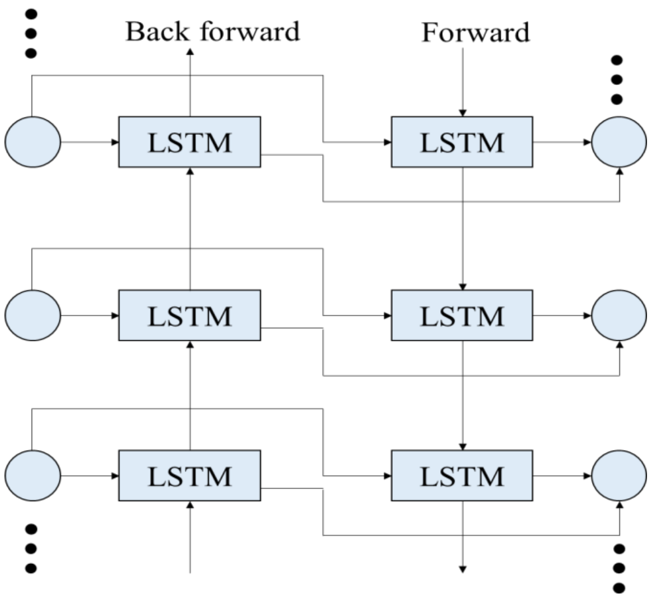
$$\{f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right)\ i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i)\ \tilde{C}_t = tanh(W_c.[h_{t-1}, x_t] + b_c)\ C_t = f_t * C_{t-1} + i_t * \tilde{C}_t\ O_t = \sigma(W_o.[h_{t-1}, x_t] + b_o)\ h_t = O_t * tanh(C_t) \qquad [7]$$

The weight matrices and bias are represented as W_i, W_f, W_o, W_c, b_i, b_f, b_o, and $b_c$respectively. The sigmoid function is represented by σ, the input vector is x_t. The h_{t-1} is the hidden layer's output at $t-1$; C_t is the cell state at t; o_t is the output of the output gate at t ; and h_t is the hidden layer's output at t.

In a BiLSTM architecture, the training sequence consists of a forward and backward-propagating LSTM [30]. The output layer's neuron receives comprehensive temporal dependencies from the two LSTMs that are simultaneously connected to it. Figure 3.a depicts the BiLSTM block utilized in this study and Figure 3.b depicts the internal structure of an LSTM cell. Each output neuron's input contains forward and reverse LSTM layer output. Equation (8) shows the output calculation formula:

$$h_t = [\vec{h}_t, h^{\leftarrow}{}_t] \qquad [8]$$

The outcome of the forward and backward networks at t are represented by $\vec{h}_t$ and $h^{\leftarrow}{}_t$, respectively.



a)

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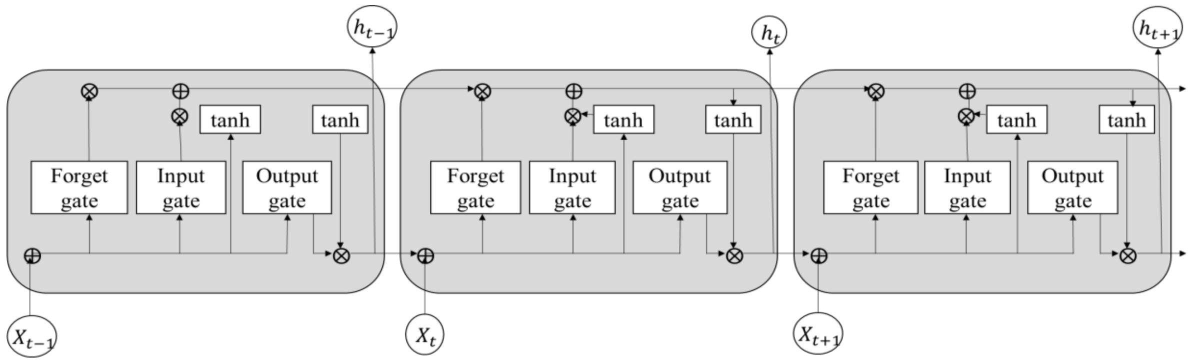

b)

Fig. 3. a) BiLSTM architecture b) Internal structure of LSTM cell

When applied to ECG signal analysis, the classic Transformer model utilizes a masked MHA mechanism that enables the model to pay attention to previous temporal dependencies while constructing a series. This ensures that the final ECG signal representation accurately captures the underlying cardiac patterns. When analyzing ECG data, the correlation between waveform segments in a sliding window. The residual connections are employed to handle the input sequence data, while BiLSTM replaces the attention layer in the actual Transformer decoder. This modification addresses the long-term dependencies issue associated with sequential data while retaining the encoder's information. To minimize overfitting during model training, the BiLSTM layer includes a Dropout gate, which randomly drops certain neurons' outputs. The final forecast is generated using a fully connected feed-forward neural network. Figure 4 depicts the architecture of the hybrid Transformer with the MHA-BiLSTM model.

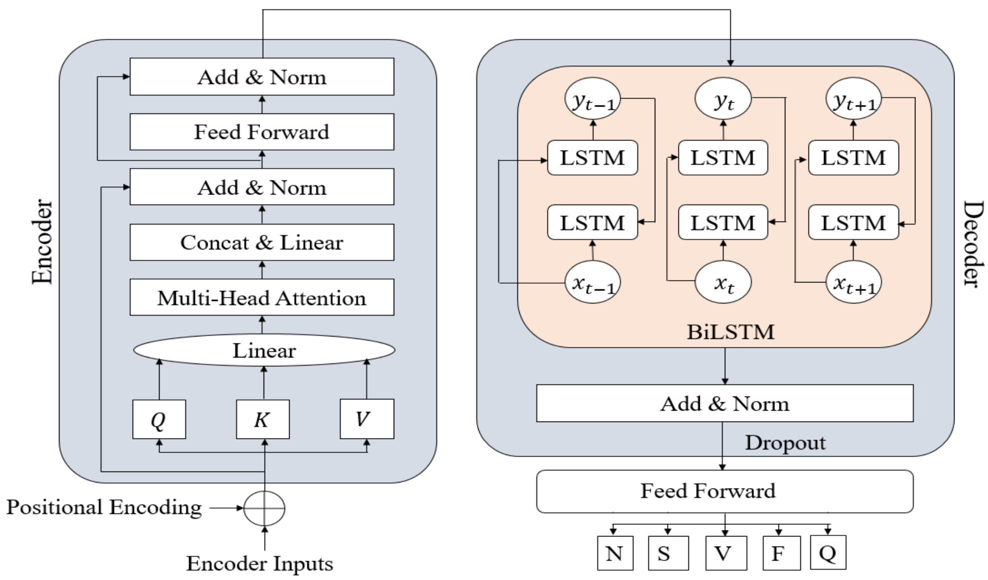

Fig. 4. Proposed Transformer with MHA-BiLSTM architecture

III. RESULT AND DISCUSSION

A. *Experimental Setup*

The experiment was performed on a PC with an AMD Ryzen R7-8840U processor running at 5.10 GHz, 16MB cache, and 8 cores, along with 16GB of RAM. The program was implemented in MATLAB version R2024b. The proposed model was trained and validated using 1,050 and 300 samples, respectively, from each category (N, S, V, F, Q) of ECG signals. For training, the samples were provided in batches of 32, and the proposed approach was executed for 100 epochs. Finally, the proposed model was tested using 150 samples from each category. For performance evaluation, metrics such as accuracy, precision, recall, F1-score, false positive rate (FPR), and false negative rate (FNR) were used [31, 32]. The formulas used to calculate these metrics are provided in the equations.

B. Experimental Outcome

The proposed Transformer-BiLSTM model was compared with traditional DL models, including Transformer, BiLSTM, and pre-trained CNN models like ResNet. The confusion matrix obtained for all four DL models is presented in Figure 5. The proposed network correctly predicted N, S, V, F, and Q categories with 150, 148, 149, 150, and 145 ECG samples, respectively. The network mistakenly classified 2 ECG samples from the N and V categories as F, and 1 sample from category S was incorrectly classified as N, V, and F. Additionally, 1-Q sample was misclassified as V. In total, the number of correct and incorrect predictions was 742 and 8, respectively.

For the other models, the Transformer correctly classified 722 samples and misclassified 28, CNN achieved 703 correct predictions and 47 incorrect ones, while Bi-LSTM resulted in 716 correct and 34 incorrect predictions. The confusion matrix provides insights into the effectiveness of the proposed network in accurately classifying heartbeats compared to other traditional models.

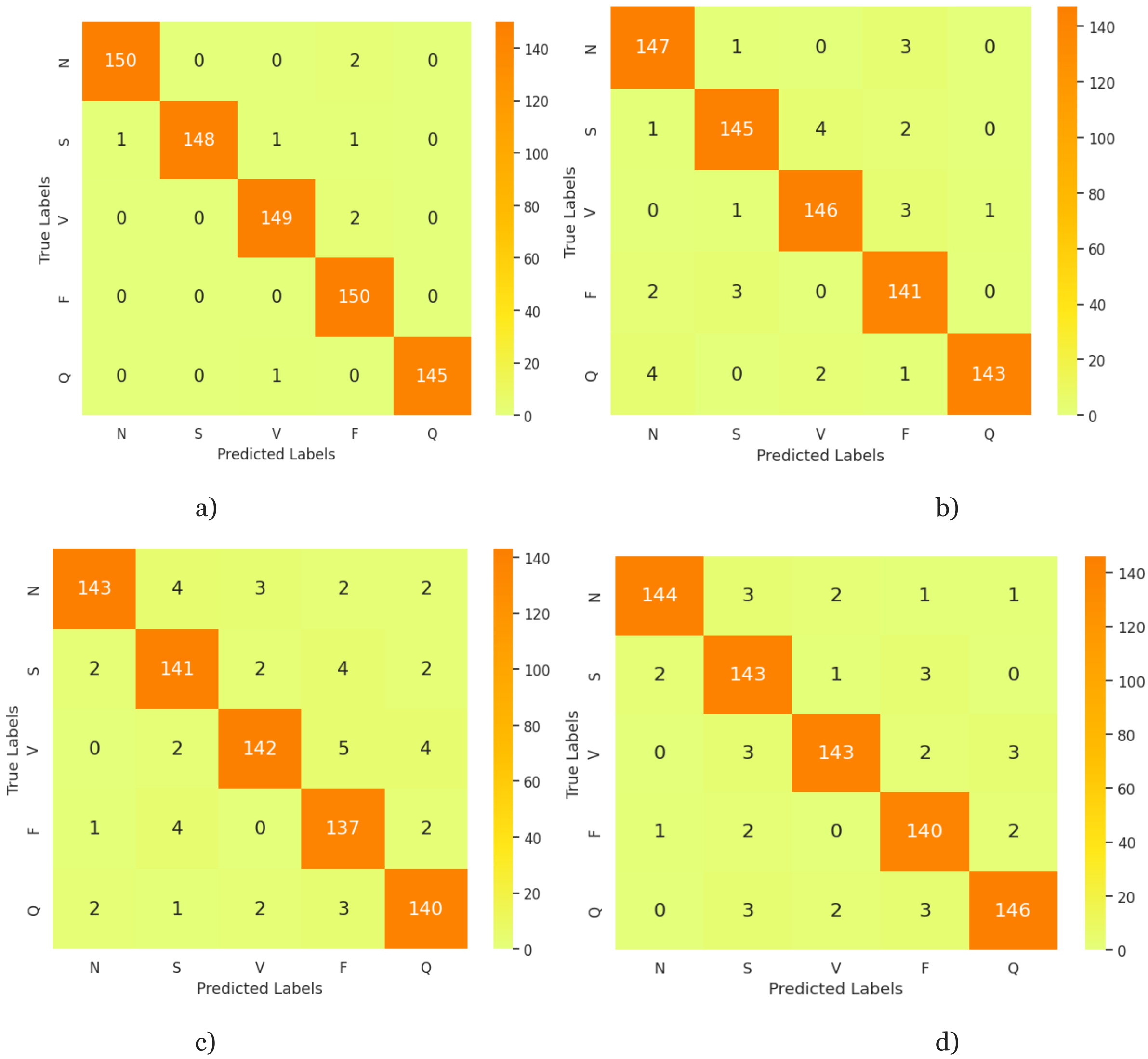

Fig. 5. Confusion Matrix of DL Model a) Proposed Network, b) Transformer, c) CNN, d) Bi-LSTM

Using elements from the confusion matrix, performance metrics for each model were calculated. The proposed network achieved an accuracy of 98.93%, whereas the Transformer model attained 96.27%, CNN 93.73%, and

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BiLSTM 95.47%. In addition to accuracy, other performance measures were also significantly higher for the proposed network. The performance metrics of all DL models are summarized in Table III. The proposed network achieved Precision, Specificity, Recall, and F1 Score of 98.96%, 99.73%, 98.94%, and 98.94%, respectively. The proposed network attained 100% precision and specificity for the S and Q ECG categories. Next to the proposed network, the highest performance was achieved by the Transformer model, with a Precision of 96.3%, Specificity of 99.07%, Recall of 96.27%, and F1 Score of 96.27%. In addition to positive performance metrics, negative metrics (FPR and FNR) were also evaluated. The proposed network exhibited a very low FPR of 1.06% and FNR of 0.27%, whereas CNN recorded the highest FPR and FNR of 6.24% and 1.56%, respectively.

TABLE III. PERFORMANCE COMPARISON OF DL MODELS ON HEARTBEAT CLASSIFICATION

Model	Class	Precision (%)	Specificity (%)	Recall (%)	F1 Score (%)	FPR (%)	FNR (%)
Proposed Model Accuracy=98.93 %	N	99.34	99.83	98.68	99.01	1.32	0.17
	S	100.00	100.00	98.01	99.00	1.99	0.00
	V	98.68	99.67	98.68	98.68	1.32	0.33
	F	96.77	99.17	100.00	98.36	0.00	0.83
	Q	100.00	100.00	99.32	99.66	0.68	0.00
	Average	98.96	99.73	98.94	98.94	1.06	0.27
Transformer Accuracy=96.27 %	N	95.45	98.83	97.35	96.39	2.65	1.17
	S	96.67	99.16	95.39	96.03	4.61	0.84
	V	96.05	99.00	96.69	96.37	3.31	1.00
	F	94.00	98.51	96.58	95.27	3.42	1.49
	Q	99.31	99.83	95.33	97.28	4.67	0.17
	Average	96.30	99.07	96.27	96.27	3.73	0.93
CNN Accuracy=93.73 %	N	96.62	99.16	92.86	94.70	7.14	0.84
	S	92.76	98.16	93.38	93.07	6.62	1.84
	V	95.30	98.83	92.81	94.04	7.19	1.17
	F	90.73	97.69	95.14	92.88	4.86	2.31
	Q	93.33	98.34	94.59	93.96	5.41	1.66
	Average	93.75	98.44	93.76	93.73	6.24	1.56
Bi-LSTM Accuracy=95.47 %	N	97.96	99.50	95.36	96.64	4.64	0.50
	S	92.86	98.17	95.97	94.39	4.03	1.83
	V	96.62	99.17	94.70	95.65	5.30	0.83
	F	93.96	98.51	96.55	95.24	3.45	1.49
	Q	96.05	98.99	94.81	95.42	5.19	1.01
	Average	95.49	98.87	95.48	95.47	4.52	1.13

The comparison of the proposed hybrid network with existing models demonstrates that the proposed network delivers promising results in abnormal heartbeat classification. Additionally, the proposed network was compared with recent research works, as presented in Table IV. Many recent studies failed to evaluate negative metrics, which are crucial for a comprehensive model analysis. Among existing studies, references [34, 35, 38, 40] utilized various models such as Residual Dense-based CNN, LSVM, Autoencoder-LSTM, and General Sparse Neural Network CNN-BiLSTM, achieving accuracy above 98%. The highest reported accuracy was 98.57% in reference [35]. However, the proposed network outperformed the reference [35], further highlighting its efficiency in abnormal heartbeat classification using ECG signals.

TABLE IV. COMPARISON OF PROPOSED NETWORK WITH THE STATE-OF-ART MODELS

Ref	Model	Accuracy	Recall	Precision	F1-Score	Specificity
[33]	2D-CNN	95.30	95.27	95.29	-	98.82
[34]	Residual Dense based CNN and LSTM	98.1	97.5	-	98.2	98.8
[35]	Autoencoder-LSTM	98.57	97.98	97.55	-	-
[36]	BiLSTM, MHA mechanisms, Depthwise Separable Convolution	94.41	92.41	92.41	-	-
[37]	Multi-Stage Dual-Swin Transformer with Attention Mechanisms	96.01	93.02	-	89.14	94
[38]	General Sparsed Neural Network	98	98	98	98	-
[39]	CNN	97.8	97	-	-	97.32
[40]	CNN-Bi-LSTM	98	91	-	-	90.96
[41]	Convolution and Residual with Skip Connection	97.3	97.3	97.2	97.2	99.3
[42]	CNN	97.91	97.91	98.09	97.98	-
Ours	Proposed nETWORK	98.93	98.94	98.96	99.66	99.73

IV. CONCLUSION

The research aims to design a highly reliable automatic abnormal heartbeat classification system using ECG signals. To achieve this, a hybrid DL model, Transformer with MHA-BiLSTM, is proposed. The proposed model helps extract the most important long-term and temporal features from the ECG signal. The ECG data is collected from the MIT-BIH database, and several pre-processing steps are performed, including interpolation, denoising, normalization, and data balancing. The processed signal is fed into the proposed network and other traditional DL models for performance comparison. The proposed model and other models are tested with 750 ECG samples. The proposed network correctly predicts 742 samples, achieving the highest accuracy of 98.93% and the lowest FPR and FNR of 1.06% and 0.27%, respectively. Other models, such as Transformer, CNN, and Bi-LSTM, achieve accuracies of 96.27%, 93.73%, and 95.47%, respectively. The proposed network is compared with state-of-the-art methods to ensure its effectiveness over others. The results demonstrate that the proposed network provides promising outcomes in heartbeat classification using ECG signals and can contribute to advancements in the healthcare sector.

In this research, only the MIT-BIH dataset is utilized. To evaluate the model's robustness, it should be tested on a variety of datasets. Additionally, only a few heartbeat abnormalities are detected, while many other abnormalities exist. In the future, the model will be extended to classify more than 20 abnormal heartbeat types.

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