Received: March 13, 2024. Revised: April 15, 2024.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Electrocardiogram Based Arrhythmia Classification Using Long Short-Term Memory with Luong Attention Mechanism

Harikrishna Mulam[1]* **Venkata Rambabu Chikati[1]** **Bhargav Salugu[1]**

[1]*Department of Electronics and Instrumentation Engineering,*
VNR Vignana Jyothi Institute of Engineering & Technology, Hyderabad, India
* Corresponding author's Email: harikrishna_m@vnrvjiet.in

Abstract: The Electrocardiogram (ECG) serves as a crucial indicator of diverse cardiac conditions, emphasizing the importance of precise signal classification for automated arrhythmia detection. ECG is an efficient tool for the diagnosis and detection of arrhythmia. Detecting arrhythmias in extended ECG segments can result in episodes being overlooked. However, since ECG transmits a massive amount of information, it becomes very complex and challenging to extract the relevant information from visual analysis. To overcome this problem, this research proposes Long Short-Term Memory (LSTM) with Luong Attention Mechanism approach for the classification of arrhythmia from ECG into 5 classes. When LSTM is combined with Luong attention, they can learn which parts of the ECG signal are crucial at each time step, and effectively capturing both short-term and long-term dependencies. For evaluating the performance of the proposed method, the data is collected from a benchmark dataset called the MIT-BIH dataset. After the collection of the dataset, the pre-processing is done using Continuous Wavelet Transform (CWT) to reduce the low and high-frequency noise. After that, the pre-processed data is forwarded to the feature extraction process to extract the relevant features by using the statistical (Skewness, Kurtosis, Moment, etc.) and time-frequency domain features. Finally, the LSTM is used to classify the arrhythmia classes. From this analysis, the proposed LSTM with Luong Attention Mechanism achieved better results in overall metrics. The proposed method achieves the accuracy of 99.75% which is comparatively higher than the existing approaches like Deep Residual Convolutional Neural Network (DRCNN) and Depth wise Separable CNN with Focal Loss (DSC-FL-CNN).

Keywords: Arrhythmia, Continuous wavelet transform, Long short-term memory, Luong attention mechanism, Statistical features.

1. Introduction

The electrocardiogram (ECG) is a non-invasive diagnostic tool that provides crucial pathological data about heart conditions, playing a pivotal role in the classification of cardiovascular diseases (CVDs) [1, 2]. Electrocardiogram (ECG) is a non-invasive technique to record the heart's electrical activity, which is measured by the set of electrodes and is significantly utilized for diagnosis as well as monitoring cardiovascular diseases. The arrhythmia events can be determined from ECG recordings using the number of computerized approaches introduced for ECG analysis [3]. Arrhythmia may cause symptoms such as palpitations, feeling dizzy, fainting as well as breath shortness. There are various types of arrhythmias named premature ventricular contractions, excessive supraventricular ectopic as well as atrial fibrillation, which are related to many cardiovascular diseases like heart attack and stroke [4, 5]. An arrhythmia can be detected by various diagnostic tools such as traditional and non-invasive [6]. Electronic Health Record (EHR) systems have become a well-known convenient means of transferring medical data among different healthcare organizations. The continuous recording and analysis of the multi-channel ECG signals is significant and required to obtain an accurate diagnosis of the heart attacks [7, 8].

Traditional arrhythmia classification depends upon the ECG signal morphology obtained from the algorithms of feature extraction [9]. The QRS complex of ECG signals contains useful information that is required to classify cardiac arrhythmias, and the handcrafted features are extracted from the QRS complex. However, the Artificial Neural Network (ANN) is capable of learning the features for classification by training [10, 11]. The statistical features named variance, kurtosis, skewness and so on are estimated from the ECG segmentation to categorize abnormal heartbeats from normal utilizing Machine learning (ML)-based classification algorithms [12, 13]. To enhance the performance and dimensionality reduction, various Deep learning (DL) approaches have been developed [14, 15]. The Convolutional Neural Network (CNN)-based models are developed to analyze the ECG time-series signals for arrhythmia classification [16, 17]. However, since ECG transmits a massive amount of information, it becomes very complex and challenging to extract the relevant information from visual analysis. In this research, the Long Short-Term Memory (LSTM) with Luong Attention Mechanism is proposed for the classification of arrhythmia disease based on the Association for an Advancement of Medical Instrumentation (AAMI) endorsement. Through permitting the model to selectively attend to relevant parts of an input, the Luong attention mechanism enhances the model's performance in capturing refined patterns as well as abnormalities in ECG signal. Based on AAMI, the arrhythmia can be classified into five categories such as sinus mode (N), Supraventricular Ectopic Beats (SVEB), Ventricular Ectopic Beats (VEB), Fusion beats (F), and unclassifiable beats (Q). The Luong attention mechanism enhances the model's performance in capturing refined patterns as well as abnormalities in ECG signal. This will lead to higher accuracy in classifying arrhythmia from ECG signal. The Luong attention mechanism calculates attention weights for each encoder hidden state based on the current decoder hidden state in LSTM. The Luong attention mechanism is generally utilized for the sequence-to-sequence models. It helps the model focus on particular parts of an input sequence when generating every part of an output sequence. The major contributions of this research are listed as follows:

- The data acquired from MIT-BIH is pre-processed by removing unwanted noises and irrelevant features using Continuous Wavelet Transform (CWT). The CWT removes the baseline wandering and reduces the low and high-frequency noise channels.
- The pre-processed signal is utilized in the feature extraction process to remove irrelevant features. The statistical and time-frequency domain features are used to extract relevant features from the pre-processed signal.
- Finally, the LSTM with Luong Attention Mechanism classifier is utilized for the classification of arrhythmia signal into five classes such as N, SVEB, VEB, F and Q.

This paper is arranged as follows: Section 2 provides the related work. Section 3 presents the proposed method. The experimental results are discussed in Section 4 and Section 5 provides the conclusion.

2. Literature survey

In this section, recent research on feature extraction and classification techniques used for arrhythmia disease are discussed.

Surbhi Bhatia [18] introduced the Deep CNN (DCNN) as well as the Bidirectional LSTM (BLSTM) approach for automatic classification of the ECG heartbeats into five various sets according to American National Standard Institutes (ANSI) - Association for the Advancement of Medical Instrumentation (AAMI) (ANSI-AAMI) standard. End-to-end learning of feature extraction as well as classification was combined and performed in this hybrid approach without the extraction of manual features. The findings were compared with the outcomes from two hybrid DL approaches such as CNN-LSTM as well as CNN-Gated Recurrent Unit (GRU). The suggested approach could efficiently recognize the ECG data because the BLSTM was in control of efficiently learning the temporal data. However, the suggested approach required a large amount of data to efficiently train the modal.

Shadhon Chandra Mohonta [19] developed a DL approach for ECG based classification of arrhythmia disease. The scalogram was acquired through the CWT and was classified through the network according to signature arrhythmia. The CWT of the recordings was acquired as well as utilized to train the 2-dimensional (2D) CNN for automatic detection of arrhythmia. This method identified the five types of heartbeats normal (N), premature of atrial (A), premature ventricular contraction (V), left (L), and right (R) bundle branch block. The CWT could estimate the signals at various scales as well as it was utilized to identify the non-stationary signals. However, the suggested approach was segmented only the smaller signals.

Yi Lu [20] presented the Depth-wise Separable CNN with Focal Loss (DSC-FL-CNN) approach to automate arrhythmia classification by the imbalance ECG dataset. The FL was designed to address class imbalance issues in ECG and contributed to the enhancement of arrhythmia classification performance, particularly for those arrhythmias with the minimum samples. The suggested approach minimized the number of parameter selections and enhanced the classification performance. However, the minimized parameters were not obvious for the entire parameters because of the flattened layer existence.

Yuanlu Li [21] introduced an enhanced Deep Residual CNN (DRCNN) for automatic arrhythmias classification. Initially, an overlapping segmentation approach was utilized to divide ECG signals into segments of 5sec in duration to address an imbalanced signal among classes. A Discrete Wavelet Transform (DWT) was utilized to reduce the noise in those segments. The focal loss function was utilized to overcome the complexity of an imbalanced classification among classes. The DRCNN method demonstrates the ability to classify arrhythmia diseases effectively without the need for heartbeat extraction. However, this method had poor directionality as well as a lack of phase information.

Ehab Eesa and Xianghua Xie [22] introduced deep learning related to the multi-model system that was presented for the classification of electrocardiogram signals. The initial model was based on the combination of CNN-LSTM to collect dynamics in temporal as well as local features for ECG data. The second model concatenated some features for classical i.e. RR intervals and Higher-Order Statistics (HOS) with LSTM (RRHOS-LSTM) to efficiently highlight the abnormality heartbeat classes. Additionally, the CNN can efficiently extract the local features and boost the capability of discrimination of the developed system. This method effectively decreased the false positives of the fusion classifier by utilizing a verification network. However, the suggested approach does not perform the feature extraction process.

Sumanta Kuila [23] presented the 12-layer deep traditionally 1-dimensional CNN with Extreme Learning Machine (CNN-ELM) for the classification of the arrhythmia into 12 various heartbeat classes. The WT technique was utilized for pre-processing to normalize the frequency noises. The Genetic Algorithm (GA) was utilized for the feature selection process to select the relevant features. The ELM is simple and it contributes interpretability. However, the presented approach had considered only the accuracy performance metric to evaluate the effectiveness.

Yun Kwan Kim [24] introduced the integration of Residual Network (ResNet) with Squeeze-and-excitation block as well as Bi-directional (Bi-LSTM) for the automatic classification of the arrhythmia. The SMOTE resampling technique was utilized for solve the problem of class imbalance in the classification of arrhythmia as compared to the augmentation approaches. The integration of ResNet and SE blocks can lead to high accurate model with enhanced generalization. However, augmentation effect in SMOTE was reduced due to baseline wander as well as noise could be extended to the rhythm data.

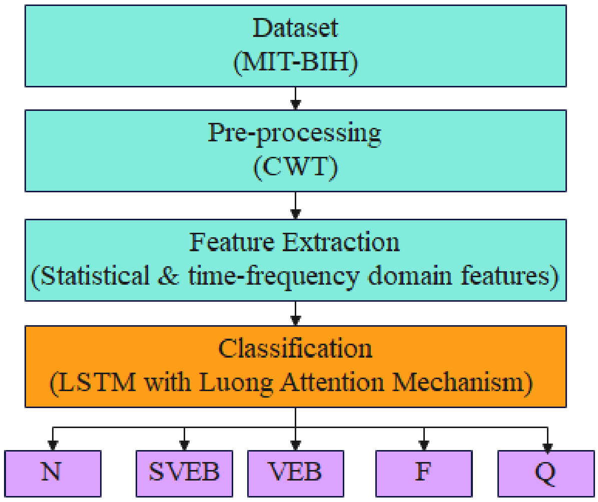

Figure. 1 Workflow of the suggested method

In this section, some limitations have been considered such as the large amount of data that needs to be efficiently trained the modal, segmented only the smaller ECG signals, minimized parameters, poor directionality as well as lack of phase information. To overcome these limitations, this research proposed the LSTM with Luong Attention Mechanism for arrhythmia detection and classification.

3. Proposed methodology

This research proposed the classification of arrhythmia disease into five categories by utilizing the DL approach of LSTM with Luong Attention Mechanism. This research comprises the four main stages: Dataset collection using MIT-BIH, Pre-processing using Continuous Wavelet Transform (CWT), Feature Extraction using CNN and finally classification using LSTM with Luong Attention Mechanism, which classifies the arrhythmia disease into five classes. Fig. 1 describes the workflow of the suggested method.

3.1 Dataset

The initial stage of the proposed method focuses on the dataset. The benchmark database of MIT-BIH [25] has been used for arrhythmia analysis and processing of ECG signals. The analog signal is digitized with a sampling frequency of 360 Hz utilizing an 11-bit analog-to-digital converter. The time of every record is 30 minutes. This dataset classified the 16 types of heartbeats and these types of heartbeats are grouped into five categories: normal (N), premature of atrial (A), premature ventricular contraction (V), left (L) and right (R) bundle branch block have been acquired from 23 recordings. These recordings have been chosen arbitrarily and there are 7500 segments in total. The 5-fold cross-validation has been utilized to estimate the proposed method's performance. The collected dataset is then provided for the pre-processing step to remove unwanted noise.

3.2 Pre-processing

The collected dataset is pre-processed before the feature extraction and classification. The collected dataset generally has irrelevant features as well as unwanted noises, which greatly impacts the accuracy of the classification method. So, the data pre-processing technique is significant for the detection and classification processes. Moreover, the pre-processing technique is used to remove the computational complexity and minimum error rates. In this pre-processing step, the CWT is used to remove the baseline wandering and reduce the low and high-frequency noise.

3.2.1. Continuous wavelet transform (CWT)

The CWT is a mathematical tool utilized for determining the signals that are continuous in time using wavelets of various classes. The CWT produces a continuous-time depiction of the signal in the time-frequency domain. It expresses the signals in wavelet function form, which are localized in the frequency as well as time domains. By permitting the translation as well as scaling wavelet parameters to modify constantly, the CWT produces a comprehensive depiction of the 1D signal. The time-frequency domain depiction $ECG_\omega\ (\alpha, \beta)$ of continuous ECG beat $ecg_{beat}\ (t)$ can be formulated in Eq. (1) as:

$$ECG_\omega\ (\alpha,\beta) = \frac{1}{\sqrt{|\alpha|}}\int_{-\infty}^{\infty} ecg_{beat}\ (t)\overline{\Psi}\left(\frac{1-\beta}{\alpha}\right)dt, where\ \alpha,\beta \in\ R \quad (1)$$

Where, α, β – scaling and translation parameter; t – time instant; $\overline{\Psi}(t)$ – continuous mother wavelet and it provides the parameters of the actual wavelet $ecg_{beat}\ (t)$. The actual ECG beats can be formulated in Eq. (2) as:

$$ecg_{beat}\ (t) = C_{\widetilde{\Psi}}^{-1}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} ECG_\omega\ (\alpha,\beta)\frac{1}{\sqrt{|\alpha|}}\widetilde{\Psi}\left(\frac{1-\beta}{\alpha}\right)ab\frac{da}{a^2} \quad (2)$$

Where, C_Ψ – wavelet constant whose value is $0 < C_\Psi < \infty$, which is expressed in Eq. (3) as follows:

$$C_\Psi = \int_{-\infty}^{\infty}\frac{\bar{\widehat{\Psi}}(\omega)\widehat{\widetilde{\Psi}}(\omega)}{|\omega|} \quad (3)$$

The combination of admissible wavelets should be 0. In this, $ecg_{beat}\ (t)$ is restored utilizing the second inverse wavelet transform which is expressed in Eq. (4) and the immediate wavelet at time t is expressed in Eq. (5) as:

$$ecg_{beat}\ (t) = \frac{1}{2\pi\bar{\widehat{\Psi}}(1)}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\frac{1}{\alpha^2}ECG_\omega\ (\alpha,\beta)e^{\left(\frac{t(t-\beta)}{\alpha}\right)}d\beta d\alpha, \quad (4)$$

$$\Psi(\mathrm{t}) = \omega(\mathrm{t})e^{lt} \quad (5)$$

Where, $\omega(\mathrm{t})$ – window. This process derives a time-frequency depiction of beats by utilizing the filter bank. The whole 2D representation is resized to 256×256 pixels. The pre-processed data can be divided into 2 parts such as 80% of the data is utilized for training and 20% for testing by using 5-fold cross-validation. Then, this pre-processed data is provided to the feature extraction process.

3.3 Feature extraction

In this step, from the pre-processed ECG signals the feature vector is extracted by using statistical and time-frequency domain features. The general aim of feature extraction is to reduce the dimensionality as well as data compaction. This will permit one to depict their data with the smaller feature subset and these features can further be leveraged to be utilized most effectively for DL applications such as diagnosis as well as classification. Furthermore, the redundant data in an entire dataset is filtered out to extract the data. Helpful features that are extracted from the signal should be capable of efficiently denoting the signal, as to either particular patterns or behaviors perceived in the signal itself. The two types of transforms such as Huang transform and Empirical Mode Decomposition (EMD) is utilized for identifying intrinsic attribute curves of ECG signals to identify Intrinsic Mode Functions (IMF) and Wavelet transform to identify an approximate coefficient vector (cAs) as well as detail coefficients vectors *(cDs).* The detailed information about the

Received: March 13, 2024. Revised: April 15, 2024.

statistical and time-frequency domain features are discussed below.

3.3.1. Statistical features

The statistical measures [26][27] such as Skewness, Kurtosis, Moment, Root Sum Square Value, Standard Deviation, Normalized First Difference, Second difference, variance, minimum and maximum entropy as well as the median can be considered for the feature extraction process. These features are utilized for IMF curves utilizing Hilbert-Huang and wavelet transforms to postulate the numerical value for all those curves, and it is utilized as the features. The statistical features are calculated by the mathematical formula in Eqs. (6)-(10) as:

$$Mean(\bar{Y}) = \frac{\sum_{i=1}^{N} Y_i}{N} \tag{6}$$

$$Variance = \frac{1}{N-1}\sum_{i=1}^{N} Y_i^2 \tag{7}$$

$$Skewness = \frac{\sum_{i=1}^{N}(Y_i-\bar{Y})^3/N}{s^3} \tag{8}$$

$$Kurtosis = \frac{\sum_{i=1}^{N}(Y_i-\bar{Y})^4/N}{s^4} \tag{9}$$

$$Entropy = -\sum_{i=1}^{N} P_i log P_i \tag{10}$$

Where, N – total number of values in the set; Y_i – every individual value in the set, where, i ranges from 1 to N; $\sum_{i=1}^{N} Y_i$ – sum of all the values in the set; $\bar{Y}$ – mean of the values; s – standard deviation; P_i – probability of ith outcome.

3.3.2. Time-frequency domain feature

In this section, Time Frequency Domain Shannon Entropy (TFDSE) features are estimated from extracted ECG signal characteristics. The Shannon entropy features are estimated from the primary 100 frequency characteristics of the time-frequency matrix of pre-processed signals. The SE for the k^{th} frequency characteristic is estimated in Eq. (11) as:

$$SE_k = -\sum_{t=1}^{L} p_t^k log_2(p_t^k) \tag{11}$$

Where, p_t^k – probability at t th bin for k th frequency characteristic which is estimated by utilizing Eq. (12) as:

$$p_t^k = \frac{h_t^k}{\sum_{t=1}^{L} h_t^k} \tag{12}$$

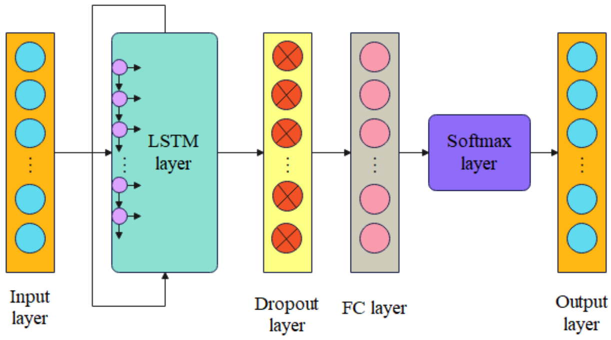

Figure. 2 The architecture of LSTM

Where, h_t^k – histogram of k th frequency component; t - t^{th} bib; In this approach, 80602 heart sound components have been estimated from the ECG signals. The output of extracted features is provided for the classification.

3.4 Classification using long short-term memory

In classification, the extracted features are utilized as input. The DL-based classification approach requires less amount of training samples and provides better performance. LSTM is the most advanced approach to forecast the time series as well as classification problems. Fig. 2 shows the general architecture of the LSTM. The time series data of every moment are utilized as input for the LSTM unit. The LSTM structure controls the state of data at every moment in the entire neural network by the structure called "gate" to attain the learning effect. The LSTM consists of three gates: input gate i_t, forget gate f_t and output gate o_t. Input gate i_t which controls the current moment of the candidate solution. The forget gate f_t which controls the value of the cell state c_t should be forgotten. The output gate o_t regulates how much information should be transformed to the next layers.

The computational procedure inside the cyclic cell structure in LSTM is as follows: Initially, compute the i_t, f_t, o_t at final moment h_{t-1} and current moment x_t, then, update the cell state c_t which is the core pf LSTM. The LSTM will gather the significant feature data for the final prediction by using the processed time series data and utilize the advantage of historical data by backpropagation procedure. The various cells in LSTM are expressed in Eqs. (13)-(18) as:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{13}$$

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{14}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (15)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (16)$$

$$h_t = o_t \odot tanh(c_t) \quad (17)$$

$$\tilde{c}_t = tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (18)$$

Where, x_t – input vector at moment t; σ – sigmoid function; W, b and h - weight matrix, bias, and hidden state vector; $\tilde{c}_t$ and c_t – input memory cell as well as cell state vector respectively. U_i, U_f U_o and U_c – weights of input, forget, output and cell state; h_{t-1} – previous hidden state at time t-1. The LSTM with attention mechanism is introduced to control difficult patterns as well as necessities. An LSTM with an attention mechanism permits an approach for focussing on the significant inputs at every time step at prediction. This approach can enhance the model's performance as well as flexibility compared to the actual LSTM approach. Dropout layer (50%) is after the LSTM layer to prevent overfitting of the model to the major class. Then, the attention mechanism distributes the LSTM weighted sum of hidden states, and it is utilized as input to the Fully Connected Layer (FCN) for estimation. The outcome of hidden states for every time step of LSTM are generated and it provided to the softmax layer to label the input ECG heartbeat, then it can be provided to the output layer.

3.4.1. Luong attention mechanism

This is an approach for computing the weights in NN limited to the Seq2Seq approach. Providing the set of hidden states $h_1, h_2, \ldots, h_n$, an attention mechanism estimates the attention weight sets $\alpha_1, \alpha_2, \ldots, \alpha_n$, that denotes a comparative significance of every hidden state in designing an outcome. The attention weights can be formulated in Eq. (19) as:

$$\alpha_t = \frac{exp(e_t)}{\sum_{k=1}^{n} exp(e_k)} \quad (19)$$

Where, e_t – a score that computes the compatibility among the target h_t as well as the decoder state s_{t-1} at before the time step. A score is estimated by utilizing one of the various functions such as dot-product, general as well as concat. A dot-product function estimates the target hidden state as well as the decoder state. The general function estimates a target hidden state as well as a linear transformation of the decoder state, which is expressed in Eq. (20) as:

$$e_t = h_t^T W_a s_{t-1} \quad (20)$$

Where, W_a – learned parameter; h_t^T – hidden state. A concat function concatenates a hidden state as well as a decoder state, then forwards a concatenation by Feedforward Neural Network (FNN) which is expressed in Eq. (21) as follows:

$$e_t = v_a^T tanh(W_a[h_t; s_{t-1}]) \quad (21)$$

Where, v_a^T – learned parameter; The attention weights are then utilized for computing the weighted sum of hidden states, which is utilized as input to the decoder state at present, which is expressed in Eq. (22) as:

$$c_t = \sum_{k=1}^{n} \alpha_k h_k \quad (22)$$

The function utilized for identifying a score ei is based on job as well as available data. Classically, a dot-product function is performed once the dimensions of hidden states are undistinguishable, as well a basic function is utilized once the dimensions are different. The concat function can collect the number of intricate connections among hidden as well as decoder states. ReLU activation function is frequently used in LSTM instead of other activation functions like sigmoid, softmax and tanh, because of better performance and computational efficiency. ReLU often performs well than alternatives in terms of training speed and model accuracy. By this classification approach, arrhythmia is classified into five classes. The classified arrhythmia signal is estimated by using experimental results.

4. Experimental results

The performance of the proposed LSTM with Luong Attention Mechanism is tested and estimated by utilizing MIT-BIH dataset and 5-fold cross-validation. All the computations are performed on MATLAB 2021a, with Windows 10, 64-bit OS, Intel Core i7- 4200U CPU processor, 16GB RAM. The proposed method is evaluated by using various performance metrices named accuracy, precision, sensitivity/recall, F1-score, specificity as well as Area Under Curve (AUC). The mathematical formula of every metric is described using Eqn. (23)-(28) as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (23)$$

$$Precision = \frac{TP}{TP+FP} \quad (24)$$

Table 1. Performance analysis of feature extraction techniques

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Specificity (%)	AUC (%)
Statistical features	91.38	89.37	89.37	87.25	86.29	87.27
Time domain features	93.38	92.93	91.20	90.45	89.91	90.45
Frequency domain features	95.26	94.28	93.19	94.29	93.92	92.29
Statistical and time-frequency domain features	99.75	96.34	99.67	99.58	99.90	95.24

Table 2. Performance analysis of various Classifiers

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Specificity (%)	AUC (%)
GAN	87.37	85.98	87.49	88.32	90.35	90.17
DNN	90.17	86.09	91.46	93.27	94.72	93.28
CNN	94.28	89.26	93.27	94.34	95.20	94.35
RNN	97.36	91.38	96.36	97.37	98.29	89.26
LSTM with Luong Attention Mechanism	99.75	96.34	99.67	99.58	99.90	95.24

Table 3. Performance analysis of LSTM with Luong Attention Mechanism with different K-fold values

K-fold values	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Specificity (%)	AUC (%)
1	93.49	91.47	90.52	93.30	94.37	86.22
3	94.26	91.36	96.38	94.38	95.46	89.37
5	99.75	96.34	99.67	99.58	99.90	95.24
8	97.87	90.93	95.46	96.33	97.09	88.38
10	98.37	91.36	97.23	98.46	98.46	89.36

$$Recall = \frac{TP}{TP+FN} \tag{25}$$

$$F1-score = \frac{2TP}{2TP+FP+FN} \tag{26}$$

$$Specificity = \frac{TN}{TN+FP} \tag{27}$$

$$AUC = \frac{\sum R_i(I_I) - I_I(I_I+I)/2}{I_I+I_f} \tag{28}$$

Where, TP - True Positive; TN – True Negative; FP – False positive; FN – False Negative; I_I – number of positive images; I_f – number of negative images; R_i – rate of ith image.

4.1 Performance analysis

This section shows the quantitative and qualitative analysis of the proposed LSTM with Luong Attention Mechanism approach with regard to various performance metrics.

Table 1 depicts the performance analysis of feature extraction algorithms Table 1 depict the performance analysis of various feature extraction methods on MIT-BIH dataset. The obtained results prove that the proposed method using Statistical and time-frequency features achieves better values for performance metrics like accuracy, precision, recall, F1-score, specificity, and AUC of about 99.75%, 96.34%, 99.67%, 99.58%, 99.90% and 95.24% respectively. The proposed method obtains better results when compared to existing methods by using CWT for removing the baseline wandering and reducing the low and high-frequency noises.

Table 2 show the analysis of the proposed LSTM with the Luong Attention Mechanism with various classifiers on MIT-BIH dataset. The proposed method's performance is measured and compared with various classifiers like Generative Adversarial Networks (GAN), Deep Neural Networks (DNN), CNN as well as Recurrent Neural Networks (RNN). These results depict that the proposed method achieves better results using various performance metrics like accuracy, precision, recall, F1-score, specificity, and AUC of values about 99.75%, 96.34%, 99.67%, 99.58%, 99.90% and 95.24% respectively. Thus, the LSTM with Luong Attention Mechanism classifier achieved better results when compared to the existing methods.

Table 3 and depict the classification results with different K-fold values of the proposed method using various performance metrics on MIT-BIH dataset. The Statistical and time-frequency domain features - LSTM with Luong Attention Mechanism achieve

Table 4. Performance analysis of heartbeat classes using LSTM with Luong Attention Mechanism

Classes	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Specificity (%)	AUC (%)
N	99.95	98.13	99.98	99.66	99.95	92.42
SVEB	99.97	95.32	98.55	99.71	99.86	97.56
VEB	99.96	97.78	99.93	99.91	99.94	96.61
F	99.93	94.63	99.96	99.88	99.87	95.47
Q	98.96	95.88	99.95	98.76	99.89	94.16

Table 5. Comparative results of the proposed method using the MIT-BIH dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Specificity (%)	AUC (%)
CNN-BLSTM [18]	98.36	89.4	94.24	91.67	N/A	N/A
2D CNN [19]	99.65	N/A	98.87	N/A	99.85	N/A
DSC-FL-CNN [20]	98.55	N/A	77.16	98.58	N/A	88.50
DRCNN [21]	88.99	56.82	52.10	N/A	94.75	N/A
RRHOS-LSTM [22]	95.81	N/A	69.20	71.06	94.56	N/A
ELM-CNN [23]	98.82	N/A	N/A	N/A	N/A	N/A
ResNet with SE block + biLSTM [24]	99.20	N/A	N/A	91.69	N/A	N/A
Proposed LSTM with Luong Attention Mechanism	99.75	96.34	99.67	99.58	99.90	95.24

better results when the K-fold value is 5 compared to the values 1,3, 8 and 10 respectively.

Table 4 depicts the performance analysis of heartbeat classes using LSTM with Luong Attention Mechanism on MIT-BIH dataset. The heartbeat classes of N, SVEB, VEB, F and Q are estimated with the performance metrices like accuracy, precision, recall, F1-score, specificity and AUC.

4.2 Comparative analysis

Table 5 represents the comparative results of the proposed LSTM with Luong Attention Mechanism method with existing methods using MIT-BIH dataset. The proposed method's performance is evaluated by utilizing evaluation metrices like accuracy, precision, recall, F1-score, specificity and AUC. These results shows that the proposed method attains the better results as compared to the other state-of-the-art methods. The Luong Attention Mechanism allows the model to apply various weights in LSTM to various parts of the input sequence. In the context of arrhythmia classification, this means the Luong attention can learn to focus more on significant segments of ECG signal.

4.3 Discussion

This research considers the detailed feature extraction and classification of Arrhythmia disease using an ECG signal. The proposed LSTM with Luong Attention Mechanism is evaluated by using the benchmark dataset namely MIT-BIH. The proposed method obtained an accuracy of 99.75% whereas an existing CNN-BLSTM, 2D CNN, DSC-FL-CNN, DRCNN, RRHOS-LSTM, ELM-CNN and ResNet with SE block + biLSTM obtained accuracy values of 98.36%, 99.65%, 98.55%, 88.99%, 95.81%, 98.82% and 99.20% respectively. The advantage of LSTM has solved the vanishing or exploding gradient problem. The attention weights generated through Luong attention mechanism provide a level of interpretability to the classification of arrhythmia. Through permitting the model to selectively attend to relevant parts of an input, the Luong attention mechanism enhances the model's performance in capturing refined patterns as well as abnormalities in ECG signal. This will lead to higher accuracy in classifying arrhythmia ECG signal.

5. Conclusion

In this research, Arrhythmia disease detection and classification is performed by using the DL approach. The LSTM with Luong Attention Mechanism is proposed to perform an efficient classification that efficiently classifies the ECG signals into five classes. Initially, the standard dataset of MIT-BIH is collected to evaluate the proposed method's performance. After the collection of data, pre-processing is performed to remove irrelevant features as well as unwanted noises by using the CWT approach. The proposed LSTM with Luong Attention Mechanism is used to classify the extracted features into five classes. The accuracy of the proposed method is 99.75%. In the future, the proposed method will extend to utilize the optimization-based segmentation process to enhance the overall accuracy results.

Notation

Variables	Description
α, β	Scaling and translation parameter
t	Time instant
$\bar{\Psi}(t)$	Continuous mother wavelet
$ecg_{beat}\ (t)$	Actual ECG beats
C_Ψ	Wavelet constant whose value is $0 < C_\Psi < \infty$
ω(t)	Window
N	Total number of values in the set
Y_i	Every individual value in the set, where, i ranges from 1 to N
$\sum_{i=1}^{N} Y_i$	Sum of all the values in the set
$\bar{Y}$	Mean of the values
s	Standard deviation
P_i	Probability of ith outcome
SE_k	Shannon entropy of k^{th} frequency
p_t^k	Probability at t^{th} bin for k^{th} frequency characteristic
h_t^k	Histogram of k^{th} frequency component
t	t^{th} bib
i_t	Input gate
f_t	Forget gate
o_t	Output gate
c_t	Cell state
x_t	Input vector at moment t
σ	Sigmoid function
W, b and h	Weight matrix, bias, and hidden state vector
$\tilde{c}_t$ and c_t	Input memory cell as well as cell state vector
U_i , U_f U_o and U_c	Weights of input, forget, output and cell state
h_{t-1}	Previous hidden state at time t-1
$h_1, h_2, \dots, h_n$	Set of hidden states
$\alpha_1, \alpha_2, \dots, \alpha_n$	Attention weight sets
e_t	A score that computes the compatibility among the target h_t as well as the decoder state s_{t-1} at before the time step
W_a	Learned parameter
h_t^T	Hidden state
v_a^T	Learned parameter
TP	True Positive
TN	True Negative
FP	False positive
FN	False Negative
I_I	Number of positive images
I_f	Number of negative images
R_i	Rate of ith image

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by 1st author. The supervision and project administration, have been done by 2nd and 3rd author.

Acknowledgments

Acknowledgments are to show that the article is supported by what organization. For example, "This work was supported by the National Nature Science Foundation under Grant No. 405".

References

[1] G. Wang, M. Chen, Z. Ding, J. Li, H. Yang, and P. Zhang, "Inter-patient ECG arrhythmia heartbeat classification based on unsupervised domain adaptation", *Neurocomputing*, Vol. 454, pp. 339-349, 2021.

[2] H. Tesfai, H. Saleh, M. Al-Qutayri, M.B. Mohammad, T. Tekeste, A. Khandoker, and B. Mohammad, "Lightweight Shufflenet Based CNN for Arrhythmia Classification", *IEEE Access*, Vol. 10, pp. 111842-111854, 2022.

[3] S. Jamil, and M. Rahman, "A novel deep-learning-based framework for the classification of cardiac arrhythmia", *Journal of Imaging*, Vol. 8, No. 3, p. 70, 2022.

[4] B.M. Mathunjwa, Y.T. Lin, C.H. Lin, M.F. Abbod, and J.S. Shieh, "ECG arrhythmia classification by using a recurrence plot and convolutional neural network", *Biomedical Signal Processing and Control*, Vol. 64, p. 102262, 2021.

[5] F.A. Reegu, H. Abas, Y. Gulzar, Q. Xin, A.A. Alwan, A. Jabbari, R.G. Sonkamble, and R.A. Dziyauddin, "Blockchain-Based Framework for Interoperable Electronic Health Records for an Improved Healthcare System", *Sustainability*, Vol. 15, No. 8, p. 6337, 2023.

[6] P. Madan, V. Singh, D.P. Singh, M. Diwakar, B. Pant, and A. Kishor, "A hybrid deep learning approach for ECG-based arrhythmia classification", *Bioengineering*, Vol. 9, No. 4, p. 152, 2022.

[7] A.O. Aseeri, "Uncertainty-aware deep learning-based cardiac arrhythmias classification model of electrocardiogram signals", *Computers*, Vol. 10, No. 6, p. 82, 2021.

[8] Z. Ahmad, A. Tabassum, L. Guan, and N.M. Khan, "ECG heartbeat classification using

multimodal fusion", *IEEE Access*, Vol. 9, pp. 100615-100626, 2021.
[9] A.H. Khan, M. Hussain, and M.K. Malik, "Arrhythmia classification techniques using deep neural network", *Complexity*, Vol. 2021, p. 9919588, 2021.
[10] S. Sowmya, and D. Jose, "Contemplate on ECG signals and classification of arrhythmia signals using CNN-LSTM deep learning model", *Measurement: Sensors*, Vol. 24, p. 100558, 2022.
[11] H. Ullah, M.B.B. Heyat, F. Akhtar, A.Y. Muaad, M.S. Islam, Z. Abbas, T. Pan, M. Gao, Y. Lin, and D. Lai, "An end-to-end cardiac arrhythmia recognition method with an effective densenet model on imbalanced datasets using ecg signal", *Computational Intelligence and Neuroscience*, Vol. 2022, 2022.
[12] S.M. Qaisar, A. Mihoub, M. Krichen, and H. Nisar, "Multirate processing with selective subbands and machine learning for efficient arrhythmia classification", *Sensors*, Vol. 21, No. 4, p. 1511, 2021.
[13] H. Li, Z. An, S. Zuo, W. Zhu, L. Cao, Y. Mu, W. Song, Q. Mao, Z. Zhang, E. Li, and J.D.P. García, "Classification of electrocardiogram signals with waveform morphological analysis and support vector machines", *Medical & Biological Engineering & Computing*, Vol. 60, pp. 109-119, 2022.
[14] J. Li, Y. Zhang, L. Gao, and X. Li, "Arrhythmia classification using biased dropout and morphology-rhythm feature with incremental broad learning", *IEEE Access*, Vol. 9, pp. 66132-66140, 2021.
[15] L.H. Wang, Y.T. Yu, W. Liu, L. Xu, C.X. Xie, T. Yang, I.C. Kuo, X.K. Wang, J. Gao, P.C. Huang, and S.L. Chen, "Three-heartbeat multilead ECG recognition method for arrhythmia classification", *IEEE Access*, Vol. 10, pp. 44046-44061, 2022.
[16] Y. Zhang, S. Liu, Z. He, Y. Zhang, and C. Wang, "A CNN model for cardiac arrhythmias classification based on individual ECG signals", *Cardiovascular Engineering and Technology*, Vol. 13, No. 4, pp. 548-557, 2022.
[17] T.H. Rafi, and Y.W. Ko, "HeartNet: Self multihead attention mechanism via convolutional network with adversarial data synthesis for ECG-based arrhythmia classification", *IEEE Access*, Vol. 10, pp. 100501-100512, 2022.
[18] S. Bhatia, S.K. Pandey, A. Kumar, and A. Alshuhail, "Classification of Electrocardiogram Signals Based on Hybrid Deep Learning Models", *Sustainability*, Vol. 14, No. 24, p. 16572, 2022.
[19] S.C. Mohonta, M.A. Motin, and D.K. Kumar, "Electrocardiogram based arrhythmia classification using wavelet transform with deep learning model", *Sensing and Bio-Sensing Research*, Vol. 37, p. 100502, 2022.
[20] Y. Lu, M. Jiang, L. Wei, J. Zhang, Z. Wang, B. Wei, and L. Xia, "Automated arrhythmia classification using depthwise separable convolutional neural network with focal loss", *Biomedical Signal Processing and Control*, Vol. 69, p. 102843, 2021.
[21] Y. Li, R. Qian, and K. Li, "Inter-patient arrhythmia classification with improved deep residual convolutional neural network", *Computer Methods and Programs in Biomedicine*, Vol. 214, p. 106582, 2022.
[22] E. Essa, and X. Xie, "An ensemble of deep learning-based multi-model for ECG heartbeats arrhythmia classification", *IEEE Access*, Vol. 9, pp. 103452-103464, 2021.
[23] S. Kuila, N. Dhanda, and S. Joardar, "ECG signal classification to detect heart arrhythmia using ELM and CNN", *Multimedia Tools and Applications*, Vol. 82, No. 19, pp. 29857-29881, 2023.
[24] Y.K. Kim, M. Lee, H.S. Song, and S.W. Lee, "Automatic cardiac arrhythmia classification using residual network combined with long short-term memory", *IEEE Transactions on Instrumentation and Measurement*, Vol. 71, p. 4005817, 2022.
[25] MIT-BIH dataset link: https://www.kaggle.com/datasets/shayanfazeli/heartbeat.
[26] S. Hadiyoso, A. Rizal, H. Fauzi, and R. Widadi, "Obstructive Sleep Apnea Detection based on ECG Signal using Statistical Features of Wavelet Subband", *International Journal of Electrical and Computer Engineering Systems*, Vol. 13, No. 10, pp. 877-884, 2022.
[27] K.V. Reddy, and N. Kumar, "Automated prediction of sudden cardiac death using statistically extracted features from electrocardiogram signals", *International Journal of Electrical and Computer Engineering*, Vol. 12, No. 5, p. 4960, 2022.