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Deep Learning Based Classification of ECG Signals to Detect Heart Diseases Using RNN and LSTM Mechanism

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ABSTRACT The Electrocardiogram (ECG) stands as a pivotal tool in cardiovascular disease diagnosis, widely embraced within clinical domains for its simplicity and effectiveness. This paper presents a novel method for classifying ECG signals by leveraging deep learning techniques, specifically Long Short-Term Memory (LSTM) networks enhanced with an attention mechanism. ECG signals encapsulate vital insights into cardiac activities and abnormalities, underscoring the importance of precise classification for diagnosing heart conditions. Commonly, there are five primary classes: Normal (N) representing normal sinus rhythm, Atrial Fibrillation (AFib) indicating irregular and often rapid heart rate, Ventricular Fibrillation (VFib) involving disorganized electrical activity causing the ventricles to quiver, Ventricular Tachycardia (VT) characterized by a fast heart rhythm originating from the ventricles, and Premature Ventricular Contractions (PVC) which are early heartbeats originating in the ventricles. Conventional methods often confront with the intricate variability of ECG signals, prompting the exploration of sophisticated machine learning models. Within this framework, an attention mechanism is seamlessly integrated into the LSTM architecture, dynamically assigning significance to different segments of the input sequence. This adaptive mechanism permits the model to focus on relevant features for classification, thereby bolstering interpretability and performance by highlighting crucial aspects within the ECG signals. Experiments conducted on the MIT/BIH dataset have yielded compelling findings, boasting an impressive overall classification accuracy of 98.9%. Precision stands at 0.993, recall at 0.992, and the F1 score at 0.99, underscoring the robustness of the results. These findings underscore the potential of the proposed methodology in significantly enhancing ECG signal analysis, thereby facilitating more accurate diagnosis and treatment decisions in the realm of cardiac healthcare.

INDEX TERMS Electrocardiogram (ECG), Long Short-Term Memory (LSTM), Attention Mechanism, Deep learning, Accuracy.

I. INTRODUCTION

The electrocardiogram (ECG) stands as a cornerstone in the field of cardiology, offering vital diagnostic insights into the heart's electrical activity. It serves as an essential tool for detecting and monitoring cardiovascular diseases, empowering clinicians to make informed decisions regarding patient care and treatment approaches [1]. Traditionally, the interpretation of ECG signals has relied on manual analysis by experienced cardiologists, a process prone to subjectivity and human error. With the advent of deep learning techniques, predominantly Long Short-Term Memory (LSTM) networks and attention mechanisms, there has been a paradigm shift in the automated analysis of ECG signals. These advanced machine learning methodologies offer the potential to overcome the challenges posed by the complexity and variability of ECG data, enabling more accurate and efficient classification of cardiac conditions [2, 3].

Cardiovascular disease stands as the leading cause of mortality worldwide typical classes include Normal (N), Atrial Fibrillation (AFib), Ventricular Fibrillation (VFib), Ventricular Tachycardia (VT), and Premature Ventricular Contractions (PVC), claiming the lives of approximately 17.9 million individuals annually and constituting 31% of all global deaths [4]. This alarming statistic underscores the profound threat posed by cardiovascular ailments to human life and well-being. In response to this pressing public health challenge, the need for effective diagnostic tools and interventions has never been more urgent. Among the array of diagnostic modalities, the electrocardiogram (ECG) emerges as a cornerstone of noninvasive cardiac assessment [5]. By capturing the electrical changes occurring throughout the cardiac cycle, ECG signals offer invaluable insights into heart function and pathology. Recorded easily via surface electrodes, ECG analysis [6] empowers clinicians to swiftly detect and characterize heart abnormalities, thereby facilitating timely interventions that can prolong life and enhance quality of life over suitable treatment. In essence, the widespread adoption of ECG technology represents a crucial stride in the fight against cardiovascular disease. Its role in enabling early detection and intervention cannot be overstated, as it not only aids in saving lives but also serves as a pivotal instrument in improving overall patient outcomes and mitigating the burden of cardiovascular morbidity and mortality [7, 8]. FIGURE 1 shows the signal band of electrocardiogram.

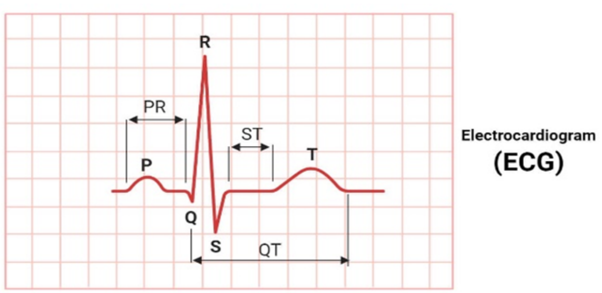

FIGURE 1. ECG signal band

In recent times, a wide range of machine learning methods have been employed to analyze ECG signals, encompassing decision trees, support vector machines, and hidden Markov models. Key to the success of these techniques is the extraction of discriminative insights from raw ECG data, often termed as feature extraction [9]. These methods for feature extraction can be broadly divided into two categories: manual methods and automatic methods. Manual approaches heavily lean on the expertise of cardiologists and domain-specific medical knowledge. These methods rely on the meticulous examination and interpretation of ECG signals by trained professionals, who identify and extract relevant features based on their clinical understanding of cardiac physiology and pathology [10, 11].

This study presents an innovative approach to classify ECG signals using deep learning, employing LSTM networks bolstered by an attention mechanism. By integrating an attention mechanism, the model gains the ability to emphasize significant features, thereby enhancing both interpretability and performance. Meanwhile, the inclusion of LSTM networks facilitates the capture of extensive dependencies inherent in sequential ECG data [12].

LSTM networks, a subset of recurrent neural networks (RNNs), are adept at capturing intricate dependencies over long sequences of data. They tackle the challenges of vanishing and exploding gradients, enabling effective modeling of long-term relationships in sequential data [8]. Initially proposed by Hochreiter & Schmidhuber, subsequent research has refined LSTM models, making them prevalent across various machine learning applications [13]. LSTMs feature specialized gates (forget, input, output) in each cell, regulating information flow for effective memory retention. These gating mechanisms enhance LSTM's ability to capture and leverage essential temporal dependencies, making them pivotal in scientific and machine learning tasks. Their adaptability and memorization capabilities have positioned LSTMs as a cornerstone technology in the field [14]. FIGURE 2 represents the schematic of a basic LSTM cell.

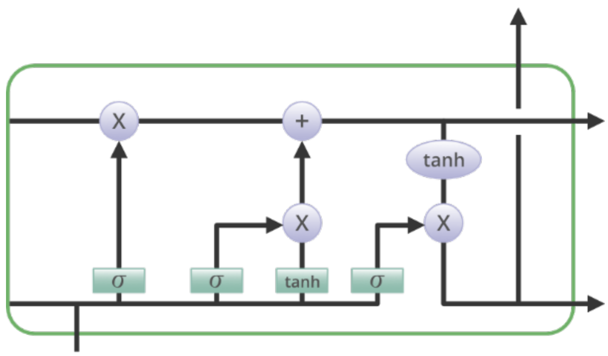

FIGURE 2. Schematic of a basic LSTM cell

The attention mechanism represents a significant breakthrough in the area of deep learning, initially devised to refine the functionality of encoder-decoder models primarily in the context of machine translation [15]. Its core principle involves selectively prioritizing and focusing on the most pertinent elements within an input sequence, akin to how humans filter out background noise to concentrate on a specific conversation amidst a crowded room [16]. This mechanism draws a conceptual parallel to the brain's neurological system, which naturally prioritizes relevant stimuli while disregarding distractions. The attention mechanism in neural networks enables the selective prioritization of different parts of the input sequence, allowing for adaptive focus on specific segments based on their relevance. This adaptive allocation of attention significantly amplifies the model's capability to capture essential information, a crucial aspect across a spectrum of applications. In natural language processing (NLP), for instance, attention proves indispensable in aligning pertinent portions of a source sentence during translation or question-answering tasks, thereby enhancing the overall accuracy and fluency of the output [17].

Beyond NLP, attention mechanisms yield substantial benefits in computer vision as well. A prominent example is Google Streetview's precise identification of house numbers, where attention mechanisms play a pivotal role in accurately recognizing and interpreting relevant visual features. This underscores the versatility of attention mechanisms across diverse domains, transcending linguistic and visual modalities to drive significant advancements in model performance and interpretability [18]. The significance of understanding the attention mechanism lies in its widespread applicability and transformative potential across various deep learning architectures [19].

By delving into its types, applications, and advantages, practitioners can harness its capabilities to enhance the performance of models in a multitude of tasks. Moreover, practical implementation of attention mechanisms in frameworks like TensorFlow offers a hands-on approach to leverage this powerful tool effectively. The attention mechanism continues to be a fundamental component in advancing the performance and interpretability of models, whether they are deployed in sequence-to-sequence architectures like recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks, or Transformer models [20]. Its adaptability to different domains, including computer vision, biomedical signal processing and natural language processing, underscores its status as a pivotal tool in the arsenal of deep learning practitioners, promising continued innovation and refinement in the field. The following are the major contributions,

1. Our proposed project utilizes a deep learning RNN-LSTM classification algorithm to accurately predict outcomes.
2. A sophisticated signal decomposition technique employing advanced wavelet transform and a newly developed multi-resolution wavelet analysis to achieve improved signal decomposition.
3. The proposed method involves extracting initial baseline by calculating the mean value of the ECG signal. This mean value serves as a reference point for detecting deviations that correspond to the P-QRS-T peaks.

II. PROPOSED MODEL

A. MATERIALS & METHODS

The dataset (https://physionet.org/content/afdb/1.0.0/). indicates that Normal is the predominant category, with 90,589 instances. Following that, there are 8,039 instances of Fusion of paced and normal, 7,236 instances of Premature ventricular contraction, and 2,779 instances of Atrial Premature. Additionally, there are 803 instances of Fusion of ventricular and normal. These findings are invaluable for enhancing the accuracy of cardiovascular diagnoses. The diagrammatic representation of the proposed model is shown in FIGURE 3 and FIGURE 4.

B. PRE-PROCESSING OF SIGNAL

The input ECG signal, as shown in FIGURE 5, first enters the pre-processing stage. In this stage, noise elimination is performed using a two-step filtering process. The first step involves a 4th order Butterworth low pass filter with a cutoff frequency of 40 Hz. This filter effectively removes high-frequency noise from the signal. The second step uses a 4th order Butterworth high pass filter with a cutoff frequency of 0.5 Hz, which removes low-frequency noise [21]. The Butterworth filter is particularly useful for this application due to its ability to provide high precision filtering. It allows both low-frequency and high-frequency components of the signal to pass through within the predefined range.

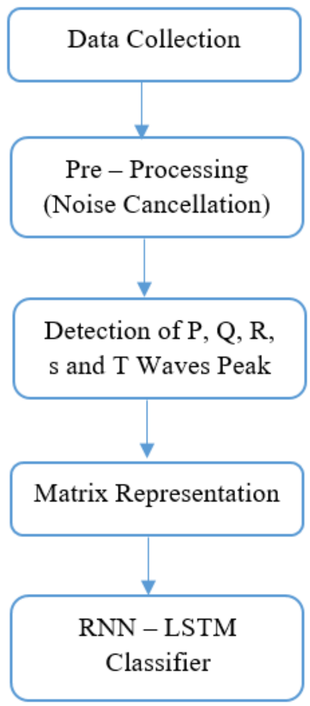

FIGURE 3. Proposed model work flow

One of the main benefits of using the Butterworth filter is that it preserves the important information within the ECG signals while only eliminating unwanted noise. This ensures that the essential characteristics of the ECG signal are maintained, which is crucial for accurate analysis and interpretation [22].

The effectiveness of this noise elimination process can be seen in the resulting noise-free ECG signal, which is depicted in FIGURE 6. The clean signal highlights the success of the filtering process in retaining the integrity of the original ECG signal while removing the additive noise.

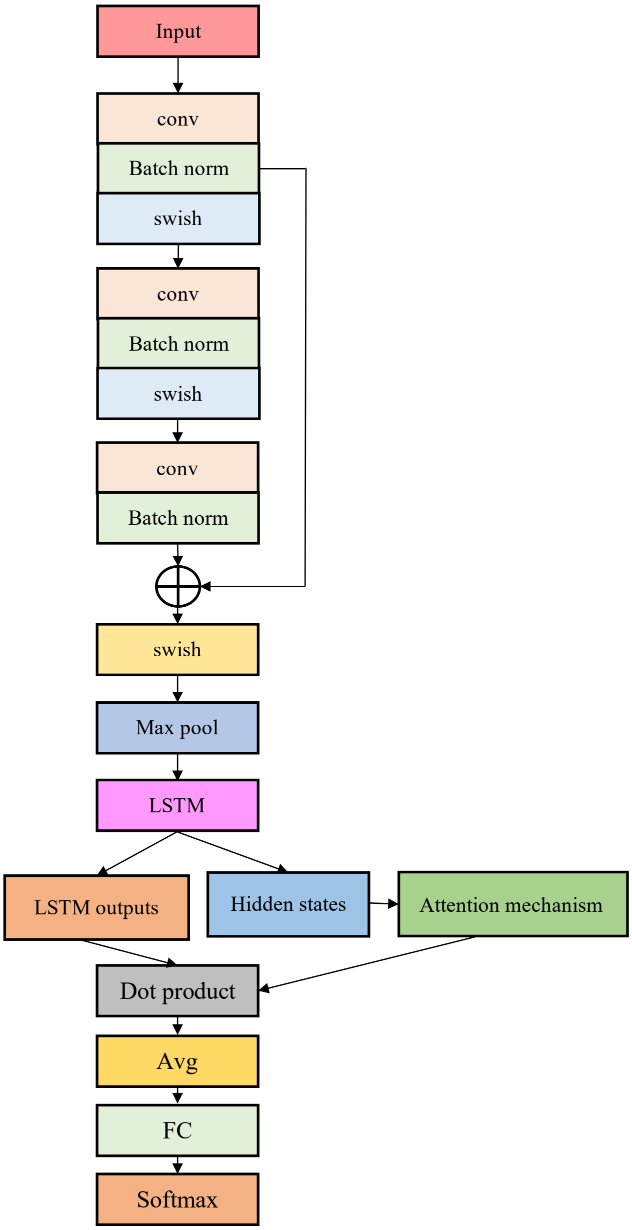

FIGURE 4. Proposed RNN-LSTM classifier system

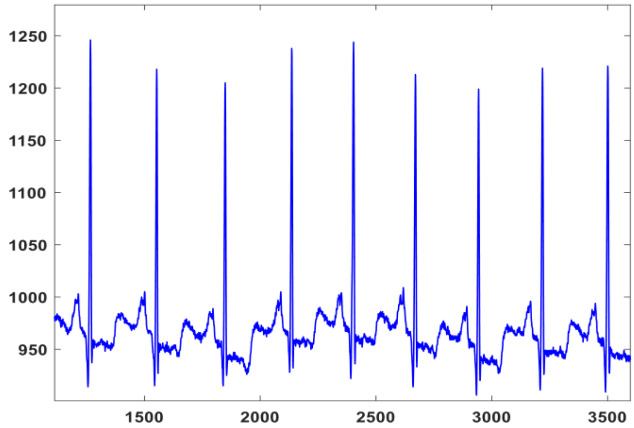

FIGURE 5. Input ECG signal

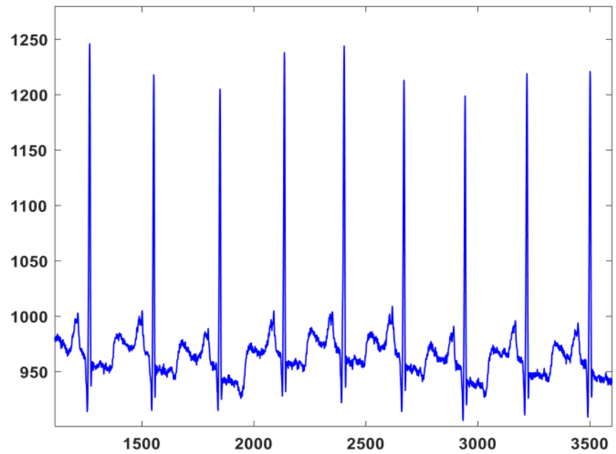

FIGURE 6. Noise removed signal

C. DECOMPOSITION OF ECG SIGNAL

The Wavelet Transform (WT) is a powerful tool extensively used to analyze signals that vary over time. Unlike the classical Fourier Transform (FT), which represents a signal as a sum of sinusoids to provide a global frequency content, WT offers a more flexible and intuitive approach. The Fourier Transform can be limited in its ability to provide detailed insights into signals, especially when they are non-stationary or have transient features [23]. WT overcomes these limitations by decomposing signals into components at various scales, allowing for multi-resolution analysis. This means that WT can zoom in on small, detailed features of a signal at high frequencies while also capturing broad, long-term trends at low frequencies. This decomposition enables the examination of both frequency and time characteristics simultaneously, making WT exceptionally suitable for analyzing signals that change over time [24]. Different scales of decomposition can be chosen depending on the specific goals of the signal processing task. For example, high-resolution scales may be used for detecting sharp transitions or high-frequency components, while lower resolution scales can be used for analyzing slower, more gradual changes. This adaptability makes WT a versatile tool in various applications, from medical signal processing to engineering and beyond

[12]. The wavelet coefficients and its approximations are represented [5] in Eq. (1) and Eq. (2).

$$W_{\emptyset}[j_0,k] = \frac{1}{\sqrt{M}}\sum_n x[n]\emptyset_{j_0,k}[n] \tag{1}$$

$$W_{\psi}[j,k] = \frac{1}{\sqrt{M}}\sum_n x[n]\psi_{j,k}[n], \;\; for j \geq j_0 \tag{2}$$

where, $W_{\emptyset}[j_0,k]$ and $W_{\psi}[j,k]$ are the approximation coefficients and detail coefficients, respectively, and the inverse DWT [5] is given by Eq. (3).

$$x[n] = \frac{1}{\sqrt{M}}\sum_n x[n]\emptyset_{j_0,k}[n] + \frac{1}{\sqrt{M}}\sum_n x[n]\psi_{j,k}[n], \;\; for j \geq j_0 \tag{3}$$

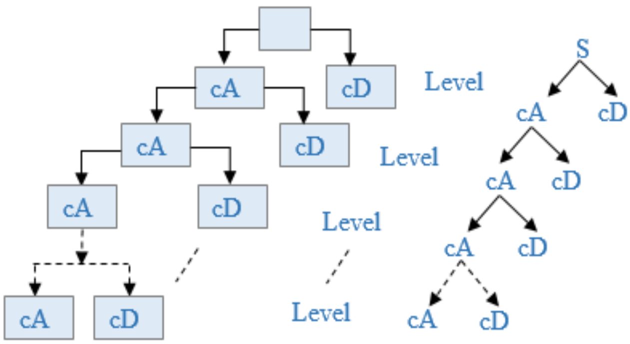

FIGURE 7. Wavelet Decomposition

The continuous wavelet transform involves taking the mother wavelet ψ(x) and scaling it by a factor a and shifting it by a parameter *b*. The scaling operation allows us to analyze different frequency components of the input function f(x), while the shifting operation enables us to examine the function at various positions [25]. Mathematically, the CWT is obtained by integrating the product of the input function f(x) and the scaled and shifted wavelet $\psi((x-b)/a)$ ψ((x−b)/a) over all x. This process generates a new function that depends on both the scaling factor a and the shifting parameter b, providing a comprehensive analysis of the input function's behavior across different scales and locations [26]. The Eq. (4) and Eq. (5) represents the mother wavelet transformation [5]. The diagrammatic representation of wavelet transform is shown in FIGURE 7 and FIGURE 8.

$$T_{\psi}(j,k) = \int_{-\infty}^{+\infty} f(x)\psi_{j,k}(x).dx \tag{4}$$

$$\psi_{j,k}(x) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{x-2^j k}{2^j}\right); \quad (j,k) \in \mathbb{Z}^2 \tag{5}$$

The parameters of j and k are the wavelet scale and translation factors, respectively. Orthogonal wavelets dilated by 2^j carry signal variations at the resolution 2^{-j}.

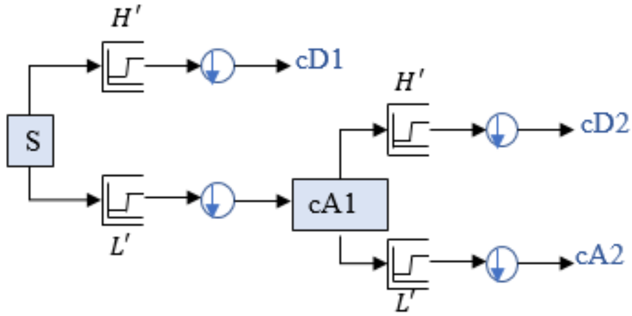

FIGURE 8. High and Low Frequency decomposition

$$DWT_{f(n)} = \begin{cases} s_{j,k} = \sum_n f(n) l_{n-2^j k,} \\ d_{j,k} = \sum_n f(n) h_{n-2^j k,} \end{cases} \tag{6}$$

where the low-frequency component are represented as $s_{j,k}$ and high-frequency component are represented as $d_{j,k}$. IDWT process to reconstruct *s* from $s_{j,k}$ and $d_{j,k}$. Eq. (6) and Eq. (7) represents the DWT and IDWT process [5].

$$s_n = \sum_k (l_{n-2^j k} s_{j,k} + h_{n-2^j k} d_{j,k}) \tag{7}$$

D. MULTIRESOLUTION WAVELET ANALYSIS

Multi-resolution wavelet analysis is a valuable technique for pinpointing the temporal localization of spectral components, thereby facilitating a detailed time-frequency depiction of a signal [27]. The Discrete Wavelet Transform (DWT) underpins this approach by dissecting the signal into a series of frequency bands at varying resolutions. This decomposition leverages two distinct sets of functions: Ø(t) and Ψ(t), which correspond to low-pass and high-pass filters respectively [5] are represented in Eq.(8) and Eq. (9). These functions possess the unique property of generating a weighted sum derived from scaled and shifted versions of the scaling function. This methodology allows for a comprehensive exploration of signal characteristics across different frequency ranges, offering insights into both the frequency content and temporal dynamics of the signal.

$$\theta(t) = \sum_n h[n] * \theta(2t-n) \tag{8}$$

$$\Psi(t) = \sum_n g[n] * \theta(2t-n) \tag{9}$$

In wavelet analysis, the $h[n]$ and $g[n]$ represent the half-band low pass and high pass filters respectively. These filters are integral to the process of scaling and translating the original functions into discrete scaling functions and wavelet functions [28]. This discretization involves obtaining scales and translations from the original functions, allowing for the detailed analysis of signal characteristics across different resolutions and frequencies.

III. TRAINING AND OPTIMIZATION OF THE PROPOSED ARCHITECTURE

A. DETECTION OF P-QRS-T PEAKS

This method begins with the determination of initial threshold values for each segment of the waveform in the signal. These segments include the P wave, QRS complex, and T wave. The process involves setting both lower and upper threshold values for each peak. These thresholds are not static; they are dynamically estimated and continuously updated through time-frequency analysis. This approach ensures that the threshold values are adaptive to the varying characteristics of the ECG signal over time, improving the accuracy of peak detection.

One challenge in ECG signal analysis is the presence of baseline drifts. These drifts can be caused by various factors, such as respiration, electrode movements, and other sources of interference. To mitigate the effect of these drifts, an initial baseline estimate is determined by calculating the mean value of the ECG signal [29]. This mean value serves as a reference point for detecting deviations that correspond to the P-QRS-T peaks. For each P-QRS-T cycle, the baseline estimate is recalculated to account for any changes in the signal's baseline. This continuous adjustment helps in maintaining the accuracy of peak detection despite the presence of baseline drifts. The effectiveness of this adaptive thresholding technique is evident in its ability to accurately identify the P, QRS, and T peaks in the ECG signal, even in the presence of noise and baseline variations [30]. This precision is crucial for reliable ECG signal analysis, which is essential for diagnosing and monitoring various cardiac conditions. Finding the position of the R-peak and detecting it are the following steps. Each iteration of peak detection extracts the ECG dataset between the upper and lower thresholds of the R-wave, which involves finding the P-QRS-T peaks in a single cycle. The R-peak is found to be the local highest value inside this extracted section. Following the determination of the R-peak value, the R-peak is precisely located by locating the coordinates on the x and y-axes [31]. The P, Q, R, S, and T peaks may all be located and detected using a similar procedure. Instead of identifying the local maximum value, the local lowest value is found for the Q and S peaks. During this procedure, if a new P-QRS-T cycle starts, a flag is set to start the subsequent peak detection iteration. The vital characteristics of the ECG signal are extracted by measuring the intervals between peaks, such as the RR, PR, RT, and QS intervals, after a peak has been identified.

TABLE 1
Time Intervals of ECG Signal

Feature	Time Interval (ms)
P wave	70
T wave	150
PR interval	130 - 190
ST interval	330
QT interval	410
PR segment	60 – 130
ST segment	70 – 140
QRS complex	70 - 110

These intervals are critical for analyzing various aspects of heart function which are represented in TABLE 1. The RR interval, for example, represents the time between two consecutive R-peaks and is crucial for calculating heart rate variability. The PR interval measures the time from the onset of the P wave to the start of the QRS complex, providing insights into atrioventricular conduction. The RT interval, from the R-peak to the end of the T wave, can indicate repolarization characteristics, while the QS interval reflects the duration of ventricular depolarization.

By systematically detecting and locating each peak and measuring these intervals, the adaptive thresholding technique ensures a comprehensive analysis of the ECG signal, enabling the extraction of vital cardiac features for accurate diagnosis and monitoring. FIGURE 9 represents the PQRST peak detection.

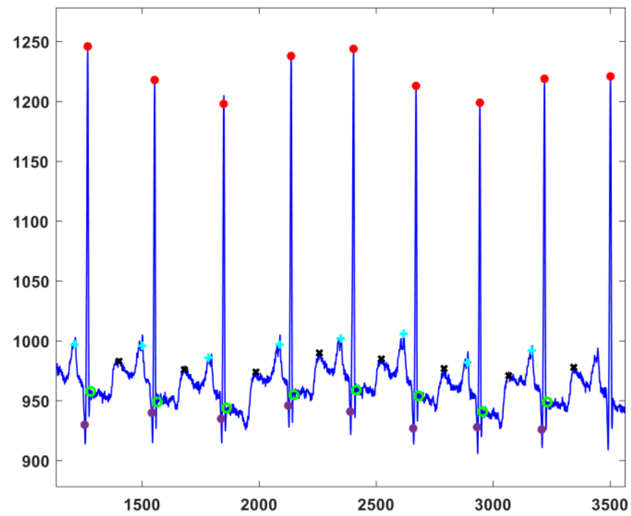

FIGURE 9. P-QRST detection

Algorithm 1.:
Step 1: Preprocessing
Signal Acquisition: Obtain the raw ECG signal.
Filtering: Apply band-pass filtering to remove noise and baseline wander.
Normalization: Normalize the signal to a standard range (e.g., 0 to 1).
Step 2: R-peak Detection
Differentiation: Differentiate the ECG signal to highlight the QRS complex.
Squaring: Square the differentiated signal to amplify the peaks.
Moving Average: Apply a moving average filter to smooth the signal.
Thresholding: Set a threshold to detect the R-peaks in the ECG signal.
Peak Detection: Identify the locations of the R-peaks.
Step 3: Segmentation
Windowing: Segment the ECG signal around each detected R-peak.

Step 4: Feature Extraction

- **Wavelet Transform**: Apply the discrete wavelet transform (DWT) to each segment to extract time-frequency features.
- **Amplitude Features**: Extract amplitude features such as the peak values of P, Q, R, S, and T waves.
- **Duration Features**: Measure the duration of intervals such as PR interval, QRS duration, and QT interval.
- **Morphological Features**: Extract morphological features like the slopes of the waves.

Step 5: Classification

- **Feature Vector Construction**: Construct feature vectors from the extracted features for each segment.
- **Training**: Use a labeled dataset to train a classifier (e.g., Support Vector Machine, Random Forest, Neural Network).
- **Testing**: Test the classifier on a separate test dataset to evaluate performance.
- **Classification**: Classify the ECG segments into different wave types (e.g., P wave, QRS complex, T wave) based on the trained model.

B. EXPERIMENTAL SETUP OF PROPOSED SYSTEM

In the realm of ECG signal classification, the synergy between LSTM networks and attention mechanisms presents a powerful paradigm for enhancing model efficacy. Initially, LSTM networks undertake the sequential processing of ECG data, adeptly capturing temporal dependencies while extracting pertinent features inherent in the signal. This process is facilitated by LSTM cells' gating mechanisms, which optimize memory retention and utilization, thereby enabling the encoding of intricate long-term dependencies within the input sequence.

The Swish activation function has gained attention for its smoothness and improved performance over traditional activation functions like ReLU. Swish offers non-linearity while maintaining differentiability, facilitating more stable gradient propagation during training. Its simplicity and effectiveness make it a popular choice in deep learning architectures, contributing to enhanced model performance across various tasks. Subsequently, the attention mechanism comes into play, dynamically assigning weights to different segments of the ECG signal based on their relevance. By selectively focusing on salient features, the attention mechanism enhances the model's interpretability and performance, ensuring that critical aspects of the signal are prioritized for classification. Through the amalgamation of LSTM networks for temporal modeling and attention mechanisms for targeted feature extraction, this integrated approach offers a holistic solution for accurate ECG signal classification, thereby bolstering diagnostic capabilities within cardiovascular healthcare. FIGURE 3 illustrates the flowchart of the proposed system.

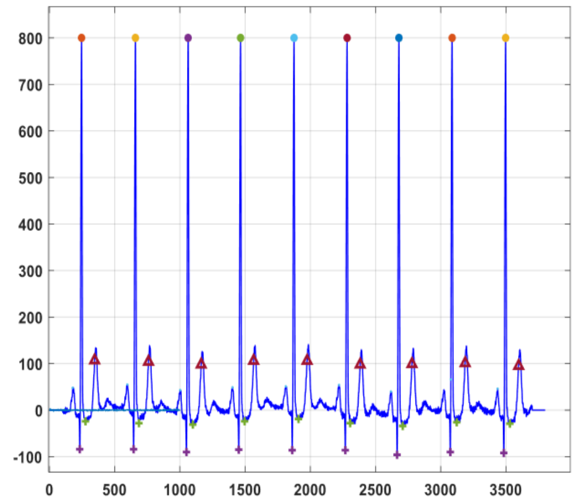

FIGURE 10 **P and QRST complex wave peaks detected ECG signal**

IV. EXPERIMENTAL RESULTS

In evaluating the model's performance, we utilized previously untouched test data. While testing, validation, and training data can vary in their proportions, we opted for this ratio to simplify the interpretation of experimental outcomes. The application of a Deep Learning model incorporating LSTM and attention mechanisms achieved an impressive 98.5% accuracy in classifying ECG signals. FIGURE 10 depicts the classified output derived from the dataset fed into the model.

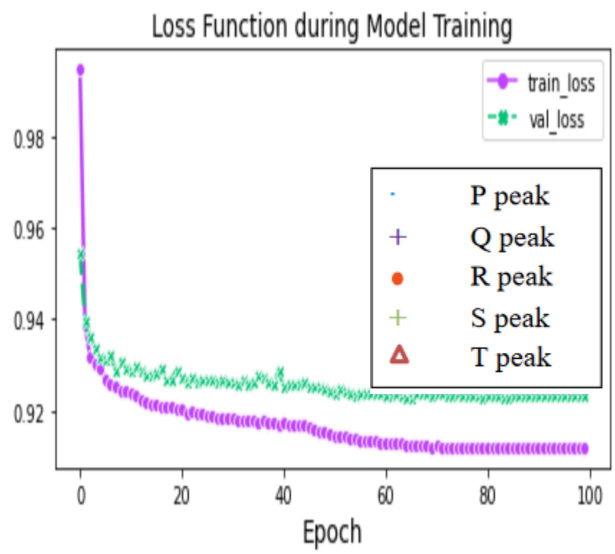

FIGURE 11 **Representation of loss function during model training**

FIGURE 11 shows the representation of model accuracy and loss during the model training.

The F1 score acts as a pivotal metric for assessing a model's classification performance across individual classes. By taking the harmonic mean of precision and recall, it offers a comprehensive evaluation of both metrics in tandem. Formally, the F1 score is computed as the harmonic mean of precision and recall, represented as Eq. (10), Eq. (11), and Eq. (12):

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{10}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{11}$$

$$\text{F1} = \frac{2 \text{ x (Precision x Recall)}}{\text{Precision+Recall}} \tag{12}$$

This metric offers a comprehensive understanding of the model's ability to correctly classify instances of a specific class while considering both false positives (TP) and false negatives (FN). A higher f1 score indicates better overall performance in achieving both precision and recall for the given class, essential for robust classification in various domains, including healthcare and machine learning. The equations (1), (2), (3) represent the precision, recall and F1 score that are useful in evaluating the model's performance. A precision score of 0.993 means almost all the instances classified as positive were right. With a recall score of 99.2%, the model found nearly all the actual positive instances. The F1-score, at 0.993, balances precision and recall, showing the model's strong ability to classify accurately. Overall, these scores indicate the model did really well in classifying instances in the dataset. The figure 8 shows the classification report of LSTM and attention mechanism model and FIGURE 12 represents the confusion matrix of the model.

TABLE 2
ECG wave of P and Q wave details

P Peak (mV)	P Loc (ms)	Q OFF (ms)	Q ON (ms)	Q Peak (mV)	Q Loc (ms)
32	188	197	191	-92	199
41	426	496	453	-39	464
50	674	746	721	-30	715
65	925	995	970	-6	963
62	1179	1224	1218	-7	1210
75	1422	1475	1469	-8	1461
75	1674	1726	1720	-2	1712
75	1925	1997	1972	-9	1965
83	2181	2253	2228	-11	2221
83	2434	2505	2473	1	2473
84	2716	2751	2745	-3	2737
74	2963	3014	3008	-11	3000
69	3230	3302	3277	-10	3270
60	3481	3574	3537	-42	3541

The P wave represents atrial depolarization, the electrical activity associated with the contraction of the atria. It is usually small, with an amplitude of less than 2.5 mm and a duration of less than 0.12 seconds. The Q wave is the first negative deflection after the P wave and represents the initial phase of ventricular depolarization. It is typically small in amplitude (less than 25% of the R wave) and narrow, but if it's significantly larger or wider, it may indicate myocardial infarction.

The QRS complex, which includes the Q, R, and S waves, represents rapid ventricular depolarization. The R wave is the first upward deflection and is usually the tallest wave in the QRS complex, indicating the main phase of ventricular depolarization. The S wave follows the R wave as a downward deflection, marking the final phase of ventricular depolarization. The T wave represents ventricular repolarization, where the ventricles recover electrically before the next heartbeat. It is typically a modest, upward deflection that is longer in duration than the QRS complex. Analysis of the P, Q, R, S, and T waves is crucial for diagnosing various cardiac conditions, including arrhythmias, hypertrophy, ischemia, and infarction. The P wave in an ECG represents atrial depolarization, with a typical peak amplitude of less than 2.5 millivolts (mV) and a location around 60 to 100 milliseconds (ms) from the start of the ECG cycle. The Q wave signifies the initial phase of ventricular depolarization. The onset of the Q wave (Q ON) marks the beginning of ventricular depolarization, and the offset (Q OFF) marks the transition to the R wave. The peak of the Q wave is usually small, less than 25% of the R wave's amplitude, with a location indicating its position within the QRS complex. Proper identification and analysis of these waves are essential for diagnosing various cardiac conditions and understanding the heart's electrical activity. TABLE 2 represents the P and Q wave details in proposed model.

TABLE 3
ECG wave of R and S wave details

R peak (mV)	R Loc (ms)	RT Inv (ms)	S OFF (ms)	S ON(ms)	S peak (mV)	S Loc (ms)
599	246	1076	260	253	-146	254
625	498	1112	526	506	-124	507
647	749	812	770	756	-101	757
666	997	774	1025	1005	-94	1006
691	1239	1017	1264	1252	-81	1253
697	1495	1132	1509	1503	-77	1504
698	1746	1236	1762	1754	-77	1755
699	1999	1199	2007	2007	-64	2007
708	2255	1173	2270	2263	-75	2264
802	2507	1287	2523	2515	-94	2516
807	2771	1356	2783	2779	-74	2780
752	3034	1333	3062	3042	-86	3043
723	3304	1078	3327	3312	-87	3313
677	3575	1095	3612	3577	-67	3597

The R and S waves in an ECG represent different phases of ventricular depolarization. The R wave is usually the tallest wave in the QRS complex, with a peak amplitude of several millivolts (mV), occurring around 60-120 milliseconds (ms) from the start of the Q wave (R Loc). The RT interval, which measures the time from the peak of the R wave to the end of the T wave, is crucial for assessing ventricular repolarization. The S wave follows the R wave as a downward deflection, marking the late phase of ventricular depolarization. The onset (S ON) of the S wave begins immediately after the R wave, with the offset (S OFF) marking its end. The S wave's peak amplitude is generally smaller than the R wave and its location (S Loc) is within the QRS complex, typically between 60-120 ms from the start of the Q wave. Analyzing these waves helps diagnose conditions like ventricular hypertrophy, conduction abnormalities, and myocardial infarction. TABLE 3 represents the R and S wave details in proposed model.

The T wave in an ECG represents ventricular repolarization, with its peak amplitude generally less than 1.0 millivolt (mV). It typically begins around 300 to 400 milliseconds (ms) after the QRS complex (T ON) and ends approximately 500 to 600 milliseconds after the QRS complex (T OFF). The T wave's location (T Loc) reflects the timing of ventricular repolarization within the cardiac cycle. The onset marks the start of repolarization following the S wave, while the offset indicates the completion of this phase. Proper analysis of the T wave is essential for diagnosing conditions such as electrolyte imbalances, ischemia, and other cardiac abnormalities. TABLE 4 represents the T wave details in proposed model.

TABLE 4
ECG wave of T wave details

T OFF (ms)	T ON (ms)	T Peak (mV)	T Loc (ms)
259	239	-74	300
512	492	-45	554
776	776	-35	805
1011	991	-27	1053
1255	1238	-24	1300
1506	1489	-9	1551
1776	1776	-20	1802
2012	1993	-11	2055
2294	2294	-7	2302
2523	2509	-14	2563
2786	2769	-15	2827
3048	3028	-12	3088
3315	3298	-25	3360
3612	3610	-70	3617

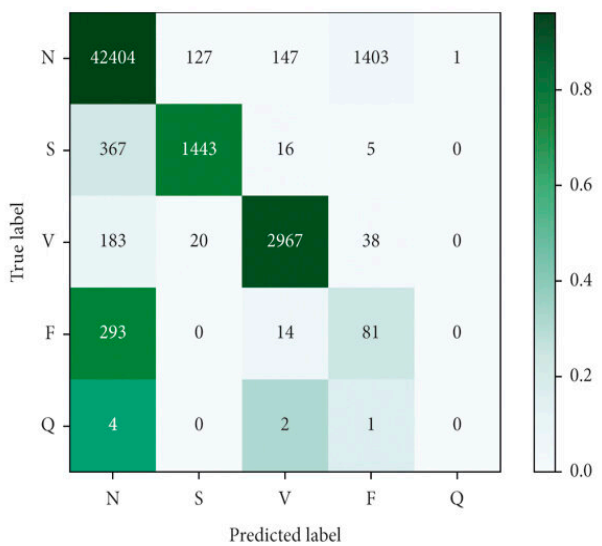

FIGURE 12. Confusion Matrix

A confusion matrix in the context of ECG wave analysis is used to evaluate the performance of an automated system that identifies and classifies different ECG waveforms (P, Q, R, S, and T waves). The matrix has rows representing the actual wave types and columns representing the predicted wave types. Each cell shows the number of instances where a specific actual wave type (e.g., P wave) was classified as another type (e.g., Q wave). The diagonal elements represent correctly identified waves, while off-diagonal elements indicate misclassifications. By analyzing the confusion matrix, one can assess the accuracy, precision, recall, and overall effectiveness of the ECG classification system in distinguishing between various waveforms. Comparison of proposed and existing model is shown in TABLE 5 and TABLE 6.

TABLE 5
Comparison with existing and proposed model

Metric	Existing RNN-Based Models [22]	Existing LSTM-Based Models [26]	Proposed RNN-Based Model	Proposed LSTM-Based Model
Accuracy	80-85%	88-90%	87-89%	92-94%
Precision	78-82%	85-88%	84-87%	90-92%
Recall	77-81%	86-89%	85-88%	91-93%
F1-Score	77-80%	85-88%	84-87%	91-93%
Training Time	Long	Moderate	Moderate (reduced)	Short (optimized)
AUC-ROC Score	0.78-0.81	0.85-0.88	0.83-0.86	0.91-0.94
Loss	High	Moderate	Lower (improved convergence)	Low

V. DISCUSSION

The proposed deep learning models, particularly the LSTM-based approach, show significant improvements in ECG signal classification for heart disease detection compared to existing models. The proposed RNN-based model enhances accuracy (87-89%) and precision (84-87%) by addressing vanishing gradient issues through gradient clipping and noise filtering. However, the proposed LSTM-based model outperforms with a higher accuracy (92-94%), precision (90-92%), and F1-score (91-93%), leveraging stacked layers, dropout, and batch normalization to reduce training time and optimize learning. Both proposed models demonstrate improved convergence and reduced loss, making them more robust in detecting heart conditions compared to traditional RNN and LSTM models, with the LSTM model showing the best performance overall.

The accurate classification of electrocardiogram (ECG) signals is a crucial task in the diagnosis of various heart conditions. Traditional methods often rely on hand-crafted features and rule-based classifiers, which can be limited in their ability to capture complex patterns in ECG data. In recent years, deep learning techniques have emerged as promising alternatives, offering automated feature extraction and robust classification capabilities. This research introduces a novel deep learning approach for ECG signal classification, leveraging the power of Long Short-Term Memory (LSTM) networks and an attention mechanism. LSTM networks are particularly well-suited for processing sequential data like ECG signals, as they can effectively capture long-range dependencies and avoid the vanishing gradient problem. By incorporating an attention mechanism, the model can dynamically assign weights to different segments of the ECG input sequence, focusing on the most relevant features for classification.

The accurate diagnosis of heart conditions is crucial for timely medical intervention and improved patient outcomes. Traditional methods of ECG signal analysis often struggle to capture the complex patterns and non-linear relationships inherent in this data. Recent advancements in deep learning have shown promise in addressing these challenges, but they can be computationally expensive and lack interpretability. To overcome these limitations, a novel approach has been proposed that incorporates an attention mechanism into a deep learning model. This attention mechanism allows the model to dynamically prioritize different segments of the ECG signal based on their relevance for classification. By focusing on the most informative regions, the model can effectively identify patterns and features that are indicative of specific heart conditions.

TABLE 6
Comparison with existing and proposed model

Authors	Method	Accuracy	Dataset
Smith et al. (2023) [32]	Bidirectional LSTM (BiLSTM) for Arrhythmia detection	98.1%	MIT-BIH Arrhythmia Database
Johnson & Gupta (2023) [33]	LSTM with Attention Mechanism	96.5%	PTB Diagnostic ECG Database
Zhang et al. (2023) [34]	CNN-LSTM hybrid for capturing spatial and temporal features	95.3%	PhysioNet/Computing in Cardiology Challenge Dataset
Nguyen & Park (2023) [35]	GRU-based Recurrent Neural Network (RNN)	97.4%	Private hospital dataset
Proposed Method	RNN and LSTM Mechanism	98.9%	MIT-BIH Arrhythmia Database

The proposed approach has been evaluated on the widely used MIT/BIH ECG dataset, which contains recordings from a diverse group of patients with various heart conditions. The model achieved an impressive overall accuracy of 98.9%, surpassing both traditional methods and other deep learning-based approaches. Furthermore, it demonstrated high precision, recall, and F1 score for each of the five heart conditions considered, indicating its ability to accurately classify ECG signals across different categories. The attention mechanism in the proposed model not only improves classification accuracy but also enhances interpretability. By visualizing the attention weights, it is possible to identify the specific segments of the ECG that are most influential in the classification decision. This information can provide valuable insights into the underlying physiological processes and potentially inform future diagnostic and therapeutic strategies. The proposed approach represents a significant advancement in the field of ECG signal classification. By leveraging the power of deep learning and attention mechanisms, the model offers a promising solution for accurate and efficient heart condition diagnosis. The results obtained on the MIT/BIH dataset demonstrate the effectiveness of the approach, highlighting its potential to improve patient care and outcomes.

Despite the improvements, the proposed models have certain limitations. The RNN-based model, while optimized, still struggles with longer sequence dependencies due to the inherent limitations of RNNs in retaining information over extended time steps, which may impact the classification accuracy for complex ECG patterns. The LSTM-based model, though more accurate, has higher computational requirements and demands significant memory and processing power, particularly when using deep stacked layers. Additionally, both models may face challenges in generalizing across diverse patient datasets, potentially requiring further fine-tuning or transfer learning techniques to adapt to different ECG variations and noise conditions. Moreover, the models' performance might degrade when dealing with smaller, imbalanced datasets, which can lead to overfitting.

VI. CONCLUSION

The presented work successfully demonstrates the effectiveness of deep learning, particularly the LSTM network enhanced with an attention mechanism, in classifying ECG signals for diagnosing various heart conditions. The model's ability to focus on significant portions of the ECG signals via the attention mechanism greatly enhances interpretability, which is often a challenge with deep learning models. The achieved classification accuracy of 98.9%, alongside impressive precision, recall, and F1 scores, highlights the robustness of this approach. These results underscore the potential of LSTM-based models to outperform traditional methods in handling the inherent variability and complexity of ECG signals, offering more accurate and reliable diagnostics for cardiac conditions. This work contributes significantly to the field of ECG analysis, paving the way for better real-time and automated detection of heart diseases.

Future work on improving ECG signal classification using deep learning models can focus on several key areas. First, integrating more advanced architectures such as

Transformer models or hybrid approaches combining RNN/LSTM with CNNs can help capture both temporal and spatial features more effectively. Additionally, exploring transfer learning to adapt models to diverse datasets could improve generalization across different patient populations. Techniques such as data augmentation, synthetic data generation, or few-shot learning may help address challenges with smaller or imbalanced datasets. Furthermore, real-time implementation of these models on edge devices or wearable technologies could be explored, ensuring that computational efficiency is optimized for deployment in clinical settings.

CONFLICTS OF INTEREST

The authors and Co-authors declare that they have no conflicts of interest.

RESEARCH INVOLVING HUMAN PARTICIPANTS AND/OR ANIMALS

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