Deep Learning-Based ECG Arrhythmia Classification Using Higher-Order Moments and LSTM

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Abstract:

Classifying arrhythmias on electrocardiograms (ECGs) is crucial for early identification and diagnosis of heart diseases. This paper describes an automated classification method that uses time-domain feature extraction and deep learning approaches to improve diagnosis accuracy. To capture heart rhythm variability, ECG data are analyzed for key properties such as heart rate, RR intervals, successive differences, standard deviation of successive differences, and root mean square of successive differences. A Long Short-Term Memory (LSTM) neural network is then used for classification, using its ability to simulate temporal relationships in sequential data. The model is trained and evaluated on a wide ECG dataset that includes numerous arrhythmia types. Performance evaluations based on criteria such as accuracy and precision show that the model is successful, with high classification rates for numerous arrhythmia classifications. While some categories remain hard, the findings show that the proposed approach is a reliable tool for supporting doctors in real-time ECG monitoring and arrhythmia diagnosis. Sudden cardiac arrest among young people is a recent global issue, and it has been shown that persons with cardiac arrhythmia are more vulnerable to a variety of heart illnesses. The study of ECG signals is critical in healthcare, notably for detecting cardiac diseases such as arrhythmia, coronary artery disease, and heart attack. To increase the quality and reliability of physiological data, blind source separation and wavelet threshold approaches were merged to create a multi-spectrum adaptive wavelet signal improvement method, which was then integrated with an enhanced blind source separation method for denoising.

keywords: Electrocardiography ; Feature extraction ; Principal component analysis ; Arrhythmia ; Wavelet transforms ; cross-domain feature extraction

I. INTRODUCTION

The yearly number of fatalities from cardiovascular diseases (CVD) in India is anticipated to increase from 2.26 million (1990) to 4.77 million (2020). [1]. Coronary heart disease prevalence rates in India have been calculated for many decades, ranging from 1.6% to 7.4% in rural populations and 1% to 13.2% in urban people[2]. Early detection of a cardiac ailment is critical since heart disease may cause sudden mortality [3]. The electrocardiogram (ECG) is a thorough and noninvasive test that contains substantial information important in discovering therapies for cardiac disorders. [4]-[5]. Arrhythmia is the most prevalent cardiovascular illness, characterized by one or more irregular heartbeats. However, because to the need for continual manual monitoring, professionals may struggle to accurately recognize the paroxysmal character of arrhythmia. An ECG is an example of a discrete, one-dimensional signal. Thus, the most natural approach to deal with ECGs is to use digital signal processing techniques. The electrocardiogram (ECG) is a record of the variations in the biopotential signal of the human heartbeat. ECG detection, which provides information about the heart and circulatory system, is critical for improving patient quality of life and providing appropriate therapy. The electrocardiogram (ECG) is a typical signal of cardiac physiology that may be used to diagnose heart diseases. Any abnormality in heart rate or rhythm, as well as a change in morphological pattern, indicates an arrhythmia, which the Medical Practitioner may manually identify. Manual observation for interpreting the recorded ECG waveform requires more time for decision making. Many cardiologists are now having trouble establishing an accurate diagnosis of ECG arrhythmia illnesses [6]. Furthermore, traditional visual analysis techniques are more complex and time-consuming. An electrocardiogram may reveal many forms of arrhythmia. It may be important for determining how well the patient is responding to therapy, thus a computerized interpretation of ECG and issues will be developed to assess the various arrhythmias using a Multimodal feature-based Machine Learning network. Clinical ECG observation might take several hours and be quite tiresome. Furthermore, visual analysis cannot be depended on, and the analyst risks missing critical information. The wide range of ECG waveform morphologies is the most challenging challenge for today's automated ECG arrhythmia analysis. As a result, multimodal feature-based machine learning for arrhythmia illnesses may be quite useful in diagnosis. Thus, our primary goal is to develop a technique with greater accuracy. This goal has driven me to research and experiment with numerous ways. Analyzing ECG data for cardiac disease identification entails a number of methodical stages. To guarantee a complete and varied dataset, ECG datasets are collected first, with an emphasis on samples associated with different cardiac diseases. This is followed by the use of Blind Source

Separation (BSS) methods, which are required for extracting Atrial Activity (AA) from raw ECG data, allowing for more accurate interpretation of particular cardiac components. After isolating the AA, a neural network model is used to extract features from the ECG data, efficiently capturing both temporal and morphological aspects. These collected properties are then loaded into a deep learning-based classification algorithm, allowing for precise diagnosis and categorization of cardiac diseases. Finally, the system's performance is assessed using a variety of metrics and compared to current approaches to confirm increases in accuracy, precision, and resilience, assuring the proposed approach's dependability in real-world clinical settings.

II. LITERATURE SURVEY

Recent research has focused heavily on automated classification of electrocardiogram (ECG) waveforms using deep learning (DL) approaches. J. Rabcan et al.[7] provide a strategy for ECG signal classification that solves the problem of information loss during preprocessing by using a fuzzy classifier in the classification step, which is meant to manage the uncertainty caused by the loss of information.

G. Pradipta et al. [8] develop an effective screening method for detecting arrhythmia (ARR) to assist physicians in diagnosing potential heart disease in fetal during pregnancy using a cross-domain feature extraction method that incorporates temporal relationships between consecutive windows, improving feature representation by examining the correlation between neighboring windows.

S. Datta et al. [9] describe a UNet-inspired autoencoder for representing and reconstructing various neurophysiological signals from single channel data.

Cardoso H. et al. [10] propose novel convergence and optimization indicators derived from Block-term Decomposition (BTD) applied to five RRI ECG segments, combined with RRI intervals (RRI), to improve the detection of Atrial Fibrillation (AF) or Normal Sinus Rhythm (NSR) using tree-based machine learning algorithms. N. Ben-Moshe et al. [11] provide a unique approach to benchmarking algorithms for single-lead ECG analysis, based on the idea that better-performing AF classification using features derived from extracted f-waves indicates better-performing extraction. S. Reddy et al. [12] proposed the Fast Independent Subspace Analysis (FastISA), Fast Independent Component Analysis (FastICA), and Join Approximate Diagonalization of Eigen Matrices (JADE) algorithms for Blind Source Separation (BSS) with rigorous pre-processing steps such as band pass filtering, wavelet denoising, orthogonalization, and Wiener deconvolution. S. Mavaddati et al. [13] suggested an effective 34-layer ResNet deep network for classifying three kinds of cardiovascular illnesses using characteristics collected from the time-frequency domain as a scalogram. J. Islam et al. [14]. We created a hybrid model using stack classifiers, which are cutting-edge ensemble machine-learning algorithms for properly classifying cardiac arrhythmias from ECG data, removing the need for considerable human involvement. Shah, A., et al.[15] suggested a self-attention artificial intelligence auto-encoder system for an efficient cardiac arrhythmia classification technique using a unique modified Kalman filter pre-processing. Abid, A. et al. [16] presented the Vision Transformer model and data augmentation approaches, a supervised model for multi-class and multi-label classification of arrhythmia in 12-lead ECG recordings, addressing data imbalance in ECG datasets.

III. METHODOLOGY

The electrocardiogram signal is high-dimensional (thousands of samples), making it useful for extracting signal characteristics. We use general signal statistics (mean, range, standard deviation, skew, kurtosis, extremes, and percentiles). We also provide domain-level characteristics depending on the lengths of the signal segments. Most of these approaches include extracting and labeling the R peaks. Robust R peak recognition in noisy electrocardiograms is not easy, and it remains an ongoing research question [17]. Electrocardiogram (ECG) data are often affected by aberrations such as baseline drift, powerline interference, and muscle noise, which may significantly impair diagnostic accuracy. Blind Source Separation (BSS) approaches, notably Independent Component Analysis (ICA), are often used to extract ECG signals from noise sources by assuming statistical independence among the original sources. Once BSS has decomposed the observed multichannel ECG into separate components, Principal Component Analysis (PCA) may be used to reduce dimensionality and extract signal-dominant components. PCA determines the key directions of variance, enabling important cardiac signal components to be retained while low-variance noise is removed. The combination of BSS and PCA therefore offers an efficient framework for ECG denoising while maintaining crucial morphological elements such as the QRS complex, P wave, and T wave, which are required for reliable arrhythmia identification and heart rate variability studies.

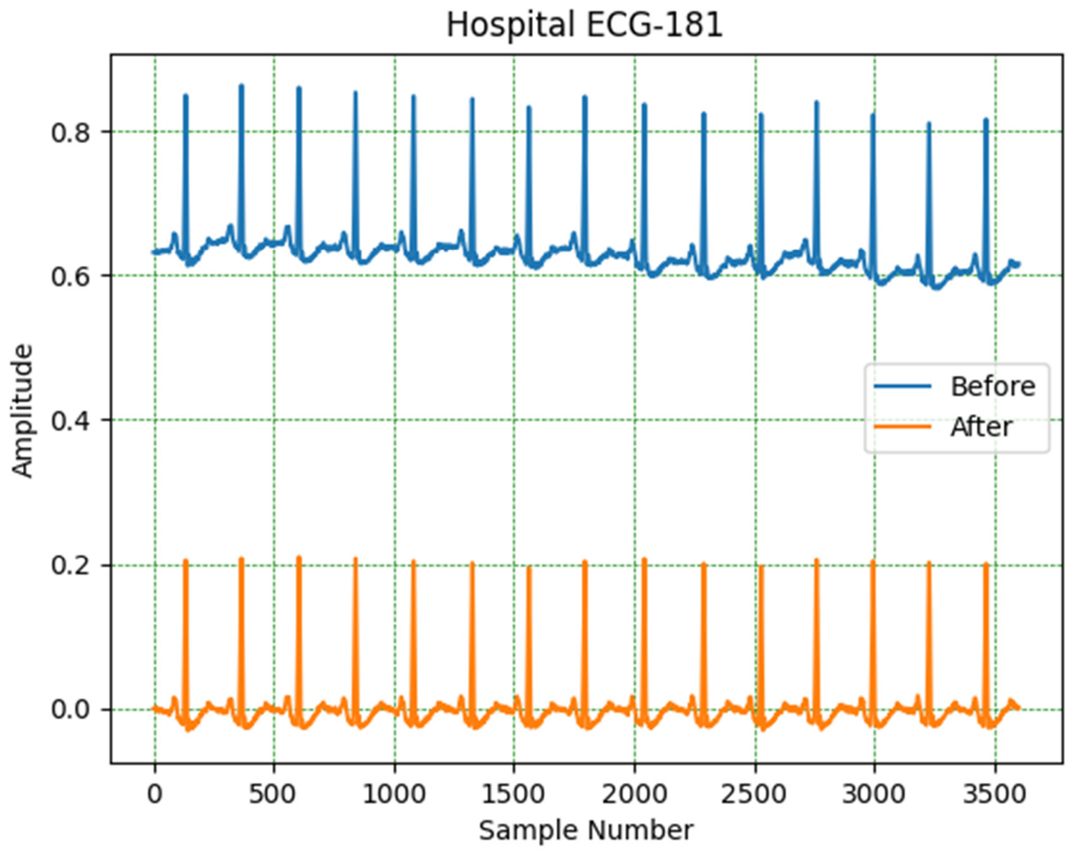

Fig: 1 Original and Denoised Signal

ECG arrhythmia classification methods extracts multiple time-domain elements from ECG data to capture the variability and irregularity of cardiac rhythms. Key components include heart rate, which represents the number of beats per minute and is a basic measure of cardiac activity, and RR intervals, which indicate the duration between consecutive R-peaks in the ECG waveform and provide information about rhythm consistency. Additional characteristics, such as Successive Differences (SD), Standard Deviation of Successive Differences (SDSD), and Root Mean Square of Successive Differences (RMSSD), are critical for assessing short-term heart rate variability. These characteristics aid in quantifying beat-to-beat variations, which are often changed in arrhythmic circumstances. A Long Short-Term Memory (LSTM) neural network is used in classification because of its capacity to represent sequential data and capture long-term dependencies in time-series signals such as ECG. The LSTM model analyzes the collected features over time, learning the temporal patterns associated with various arrhythmias and reliably categorizing the signal as arrhythmic or normal, providing a strong tool for automated and exact cardiac diagnosis.

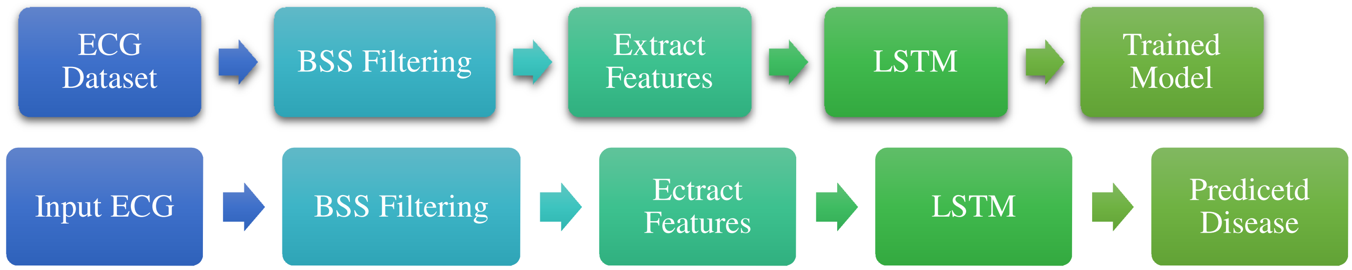

Fig: 2 Proposed System Flow

Daubechies D4 scaling function:

$$\alpha_i = h_0 s_{2i} + h_1 s_{2i+1} + h_2 s_{2i+2} + h_3 s_{2i+3}$$

$$\alpha[i] = h_0 s[2i] + h_1 s[2i+1] + h_2 s[2i+2] + h_3 s[2i+3] \quad (1)$$

Daubechies D4 wavelet function:

$$c_i = g_0 s_{2i} + g_1 s_{2i+1} + g_2 s_{2i+2} + g_3 s_{2i+3}$$

$$c[i] = g_0 s[2i] + g_1 s[2i+1] + g_2 s[2i+2] + g_3 s[2i+3] \quad (2)$$

QRS Complex and RR INTERVAL DETECTION:

1] FILTERING:

Firstly, the ECG signal is pass through the low-pass filter having transfer function is

$$H(z) = \frac{\left(1 - z^{-6}\right)^2}{\left(1 - z^{-1}\right)^2} \quad (3)$$

And the difference equation of the filter is

$$y(nT) = 2y(nT - T) - y(nT - 2T) + x(nT) - 2x(nT - 6T) + x(nT - 12T) \quad (4)$$

The output of the low-pass filter is than pass through the high pass filter having transfer function is

$$H(z) = \frac{\left(-1 + 32z^{-16} + z^{-32}\right)}{\left(1 + z^{-1}\right)} \quad (5)$$

And the difference equation of the filter is

$$y(nT) = 32x(nT - 16T) - \left[y(nT - T) + x(nT) - x(nT - 32T)\right] \quad (6)$$

Where, T=Sampling period,

N=Number of samples

The above low-pass filter may eliminate high frequencies from the signal; its cut-off frequency is around 11 Hz, and the gain is 36. While a high-pass filter may eliminate low frequencies from a signal, its cutoff frequency is around 5 Hz and gain is 3. The optimum passband for maximizing QRS energy is between 5 and 15 Hz [18]. So, by cascading low-pass and high-pass filters, a simple band pass filter may be created with a 3dB passband spanning 5-12 Hz.

2] DERIVATIVE:

The filtered ECG signal is sent into the derivative block to get the slope of the QRS complex. Because the effect of the T and P waves is greater than that of the R wave, an amplitude threshold is used to decrease their influence.

The transfer function of derivative is

$$H(z)=\frac{1}{8T}\left[-z^{-2}-2z^{-1}+2z^{1}+z^{2}\right] \tag{7}$$

And the difference equation is

$$y(nT)=\frac{1}{8T}\left[-x(nT-2T)-2x(nT-T)+2x(nT-T)+x((nT-2T))\right] \tag{8}$$

If the recorded ECG is more distorted by noise, it may be unable to identify spurious peaks, thus the derivative output is smoothed using a smoothing filter.

3] SQUARING FUNCTION:

The derivative block's output is then squared to make all samples positive while also amplifying the higher amplitude samples (i.e. QRS complexes), allowing for more efficient peak recognition.

$$y(nT)=\left[x(nT)\right]^2 \tag{9}$$

Where x(nT) and y(nT) are the input and output signals respectively.

4] PEAK DETECTION:

R peak annotation may provide important aspects for detecting arrhythmias. This includes RR interval data, heart rate, and variability aspects.

The primary goal of the aforementioned processes is to locate peaks in a signal and establish their locations and heights. It collects ECG characteristics, highlights them, and then finds the R peaks in the signal. A peak is established when the signal changes direction within a certain time span [19]. QRS complex temporal position is determined by the rising edge point of the integrated ECG Squared waveform. To identify a peak, the current sample value is kept in the temp local maximum. If the next sample value is bigger than the temp local maximum, store it there. Otherwise, if it is less than half of the temporal local maximum, a peak is found and discovered. If both of the aforementioned requirements are not met, the procedure is repeated. To distinguish the correct peak from noise, peaks preceded by a refractory blanking of less than 200ms to disregard T waves and repeated detection of QRS complex waves are ignored. Furthermore, if the peak exceeds the adaptive detection threshold, it is classified as a QRS complex rather than noise. The threshold may be computed as:

$$D_t = NP_l + C_t\left(QRS_{pl} - NP_l\right) \quad (10)$$

Where

Dt is the detection threshold, Ct is the thresholding coefficient and NPl is the level of noise peak while QRSpl is the QRS complex peak level.

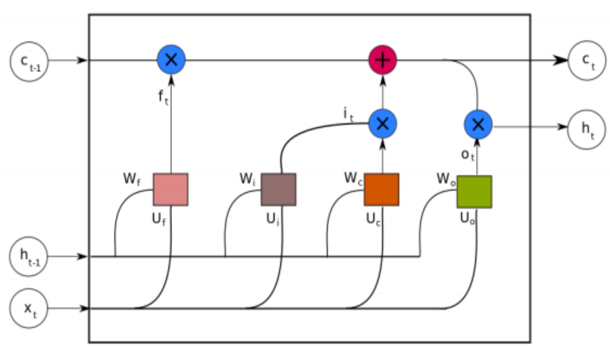

Fig 3: Memory Networks for Long-Term and Short-Term Storage

A specific kind of recurrent neural network (RNN) called an LSTM network is made to model and learn long-range dependencies in sequential data. By adding an internal memory cell and a number of gates that control the information flow, LSTMs get around the vanishing gradient issue that plagues conventional RNNs.

Together, the four primary parts of an LSTM unit—the Forget Gate, Input Gate, Candidate Memory (Cell Update), and Output Gate—manage the cell state and regulate the amount and timing of data that is added to or removed from memory.

LSTMs with four gate: forget (f), input (i), memory (c), and output gate (o).

a) Update Gate: Combines the decisions from the forget and input gates to update the cell memory.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (11)$$

- Old memory is reduced by the forget gate.
- New information is added through the input gate.

b) Forget Gate: Determines what portion of the past memory C_{t-1}, should be retained or discarded. Uses a sigmoid function to produce values between 0 and 1.

- A value close to 0 means "forget this information", while a value close to 1 means "keep it".

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (12)$$

c) Memory Gate: creates a fresh pool of possible memories.

$$\tilde{C}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (13)$$

d) Input Gate: Controls how much new information from the current input should be written into the memory cell.

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (14)$$

This is the new information that can potentially update the memory, modulated by the input gate.

e) Output Gate: Determines which part of the updated cell state should be output as the hidden state.

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

- The output gate filters the cell state and decides what to reveal at this time step.
- This filtered value becomes the next hidden state, h_t which is used in subsequent steps.

Algorithm 1: Pseudo Code

```
Define Model:
Model.add(concat Features
Model.add(LSTM)
Model.add(Dropout)
Model.add(Dense)
Model.add((Activation)
Compile Model:
Model.compile()
```

$$Accuracy = \frac{True\ Positive\ Signal + True\ Nagative\ Signal}{Positive\ Signal + Negative\ Signal}$$

$$Precision = \frac{True\ Positive\ Signal}{True\ Positive\ Signal + False\ Positive\ Signal}$$

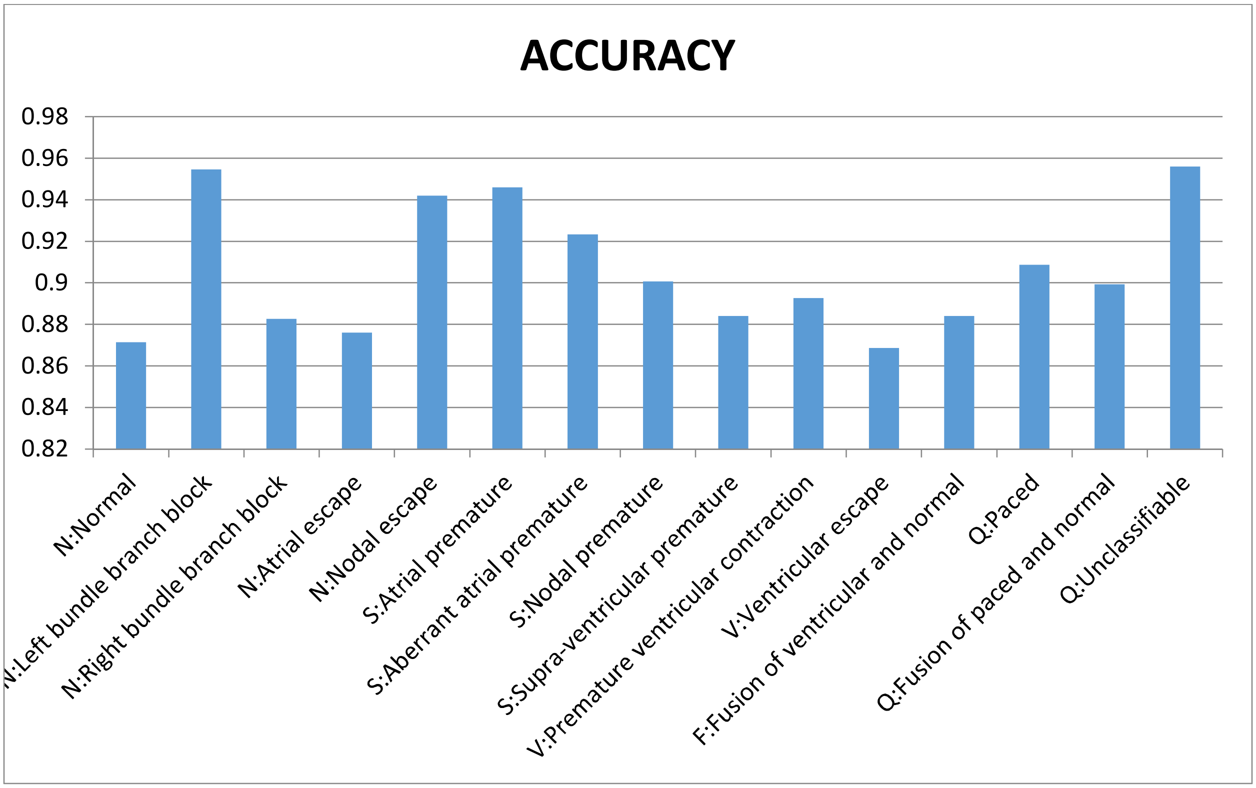

Fig: 4 Accuracy Comparison

The figure shows the classification accuracy of an ECG arrhythmia detection system for different kinds of cardiac rhythms. The model is very accurate in diagnosing numerous arrhythmias, most notably Unclassifiable and Right bundle branch block, with accuracies approaching or exceeding 0.95. Other classes, such as Atrial escape, Atrial premature, and Aberrant atrial premature, perform well with accuracies around 0.94. Meanwhile, lesser accuracies are seen for classes such as Normal, Ventricular escape, and Fusion of paced and normal, suggesting that these kinds may be more difficult to discern owing to overlapping characteristics or less distinctive patterns. Despite considerable fluctuation, overall accuracy across most classes stays above 0.88, confirming the classification model's efficacy, which is most likely due to strong feature extraction and the sequential learning capabilities of deep learning techniques like LSTM. This demonstrates the system's potential for accurate arrhythmia identification in clinical settings.

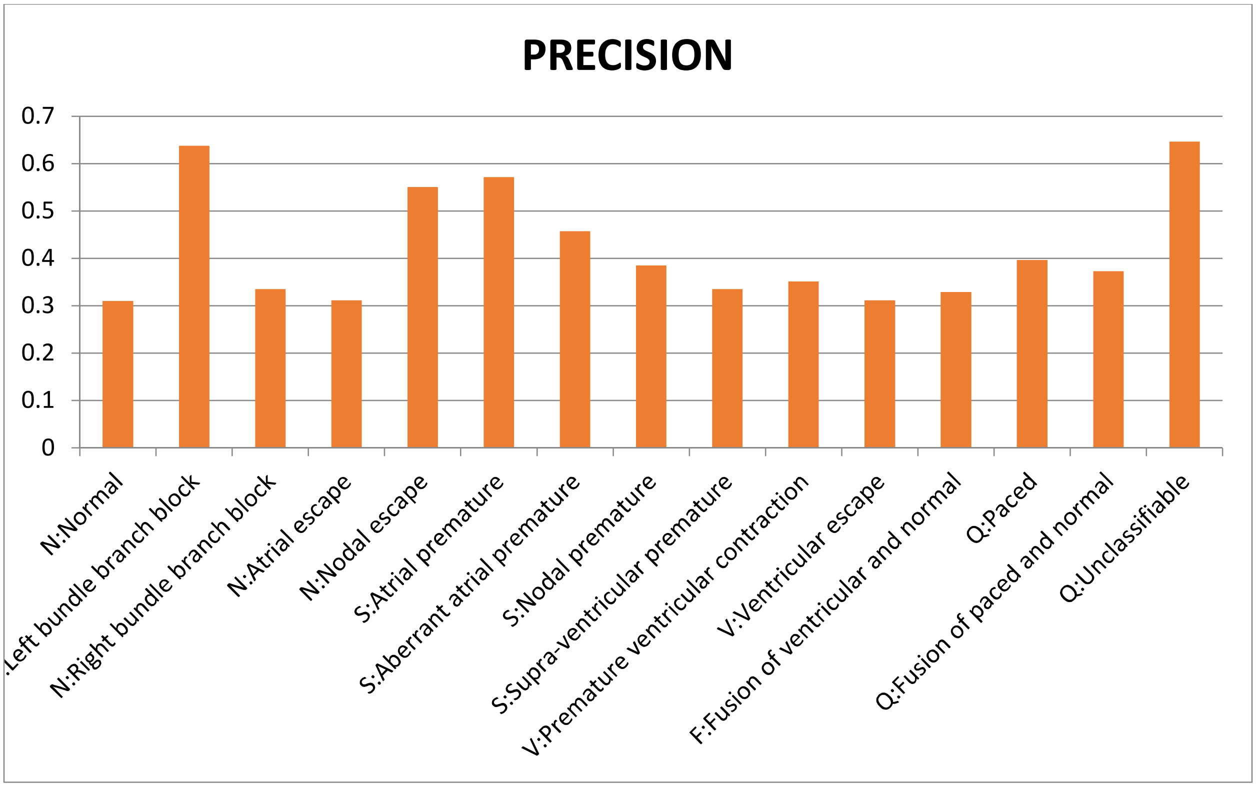

Fig: 5 Comparison of Precision

The bar chart illustrates the accuracy of an ECG arrhythmia classification algorithm across several heart rhythm categories. The model has the greatest accuracy for the Unclassifiable class, surpassing 0.65, followed by Right bundle branch block and Atrial premature, both with precision values over 0.55. various findings suggest that the model is especially good at properly recognizing true positives for various arrhythmia types. Moderate accuracy is seen in categories such as Aberrant atrial premature, Nodal escape, and Atrial escape, indicating moderately trustworthy performance in these circumstances. However, other classes, including Normal, Ventricular escape, Fusion of ventricular and normal, and Fusion of paced and normal, have lower accuracy values, often around or below 0.35, suggesting a greater likelihood of false positives in these categories. Overall, although the system performs well in several arrhythmia categories, the variability in accuracy shows the need for more refining, particularly in differentiating more ambiguous or overlapping ECG patterns.

CONCLUSION:

Finally, applying modern signal processing and deep learning methods to classify ECG arrhythmias has the potential to greatly improve the accuracy and automation of cardiac diagnosis. The system can efficiently learn temporal patterns and discriminate between distinct arrhythmia types by extracting relevant time-domain information such as heart rate, RR intervals, consecutive differences, and statistical measurements, as well as using sophisticated models such as LSTM. The assessment measures, including accuracy and precision, show that, although the model excels at recognizing some arrhythmias, such as Unclassifiable and Right bundle branch block, certain categories, such as Normal and Fusion types, remain difficult to classify. These findings highlight the approach's usefulness while also indicating areas for development, notably in increasing the model's accuracy for complicated or overlapping arrhythmias. Overall, the proposed approach advances intelligent ECG analysis systems and shows promise for real-time, non-invasive, and trustworthy cardiac monitoring.

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