ECG signal classification using CNN & LSTM with Aquila Optimization technique

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Abstract: In this research article, the development of ECG signal classification using CNN_LSTM with Aquila Optimization technique is presented along with the simulation results. The research study titled "ECG Signal Classification Using CNN & LSTM with Aquila Optimization Technique" presents a novel approach for the accurate and efficient classification of electrocardiogram (ECG) signals. In this study, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are employed as deep learning architectures to extract relevant features and capture temporal dependencies in ECG waveforms. To enhance the model's performance and convergence, the Aquila Optimization Technique is introduced, a customized optimization algorithm designed to address the unique challenges of ECG signal classification. The proposed methodology is evaluated on a diverse and comprehensive ECG dataset, and its performance is compared with existing classification methods. The results demonstrate the effectiveness of the CNN and LSTM combination, augmented by the Aquila Optimization Technique, in achieving high classification accuracy and robustness for various cardiac arrhythmia classes. This research has significant implications for the field of medical diagnostics, as it provides a promising avenue for accurate and real-time ECG signal analysis, ultimately contributing to the early detection and treatment of cardiovascular diseases.
Keywords: ECG, Bio-medical, Optimization, CNN, ANN

1. Introduction

The accurate classification of electrocardiogram (ECG) signals is a critical component of modern healthcare, aiding in the timely diagnosis and treatment of cardiovascular diseases. ECG signals, which represent the electrical activity of the heart, provide invaluable insights into a patient's cardiac health. With the advent of deep learning and advanced signal processing techniques, there is a growing opportunity to leverage artificial intelligence to improve the efficiency and accuracy of ECG signal classification. This research is centered on the development of a robust methodology for ECG signal classification, combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks with a novel optimization technique known as the Aquila Optimization Technique. The objective of this study is to enhance the classification accuracy and real-time processing capabilities, ultimately benefiting both clinicians and patients in the diagnosis and management of cardiac arrhythmias.

2. Background and Significance

Cardiovascular diseases remain a leading cause of mortality and morbidity worldwide. Early detection and classification of cardiac arrhythmias, such as atrial fibrillation, ventricular tachycardia, and bradycardia, are crucial for guiding appropriate clinical interventions and treatments. ECG, as a non-invasive and widely accessible diagnostic tool, plays a pivotal role in the early detection of these arrhythmias.

Traditionally, ECG signal analysis and classification were carried out through manual interpretation by trained healthcare professionals. While this approach has been highly effective, it is labor-intensive, time-consuming, and may be prone to human error. The need for automated ECG signal classification has spurred the development of computer-aided diagnostic systems. These systems harness the power of machine learning and deep learning techniques to process ECG data efficiently and accurately.

Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have been particularly effective in capturing complex patterns and temporal dependencies within ECG waveforms. CNNs excel at feature extraction, while LSTMs are well-suited for modeling sequential data, making them complementary in the context of ECG signal analysis. The utilization of deep learning architectures provides an opportunity to automate the process of ECG classification, minimizing the need for manual interpretation and improving the speed and consistency of diagnosis.

However, the application of deep learning models to ECG signal classification is not without its challenges. ECG signals are characterized by their high dimensionality, noise, and variations in morphology across individuals. Furthermore, training deep learning models can be computationally intensive and require careful hyperparameter tuning. To address these challenges, the research introduces the Aquila Optimization Technique, a novel optimization algorithm specifically designed for the efficient convergence and robust performance of deep learning models applied to ECG classification.

3. Research Objectives

The primary objective of this research is to develop an effective and robust methodology for ECG signal classification, harnessing the power of CNNs and LSTMs in combination with the Aquila Optimization Technique. The specific research objectives are as follows:

- To design a deep learning architecture that effectively extracts relevant features from ECG signals and captures temporal dependencies, thus enabling accurate classification of different cardiac arrhythmias.
- To implement the Aquila Optimization Technique as a customized optimization algorithm tailored to the unique characteristics of ECG data, with the aim of improving model convergence and classification accuracy.
- To evaluate the performance of the proposed methodology on a diverse ECG dataset, comparing it with existing classification methods to assess its effectiveness and generalization capabilities.
- To explore the potential for real-time ECG signal classification, with implications for improving the efficiency of clinical decision-making and patient care.

4. Structure of the Research

This research is structured into several key components, each of which contributes to the development and evaluation of the proposed ECG signal classification methodology. These components include:

Data Collection and Preprocessing: Gathering a diverse dataset of ECG signals and preprocessing the data to ensure consistency and usability for training and testing.

Deep Learning Model Architecture: Designing a hybrid deep learning architecture that combines CNNs and LSTMs for feature extraction and sequential modeling of ECG signals.

Aquila Optimization Technique: Implementing and fine-tuning the Aquila Optimization Technique to improve model convergence and classification accuracy.

Performance Evaluation: Assessing the performance of the developed model on the ECG dataset, including accuracy, sensitivity, specificity, and other relevant metrics.

Comparative Analysis: Comparing the performance of the proposed methodology with existing ECG signal classification methods to establish its effectiveness and advantages.

Real-Time Processing: Exploring the potential for real-time ECG signal classification, with a focus on the efficiency and practicality of clinical implementation.

Through these research components, we aim to contribute to the field of ECG signal classification by offering a robust, accurate, and efficient solution that can aid healthcare professionals in diagnosing cardiac arrhythmias and, ultimately, improve patient outcomes. Furthermore, this research may have broader implications for the application of deep learning and optimization techniques to other biomedical signal classification tasks, advancing the intersection of artificial intelligence and healthcare.

5. Literature Survey

The classification of electrocardiogram (ECG) signals has been a subject of extensive research, driven by the critical need to enhance the accuracy and efficiency of cardiac arrhythmia diagnosis. This literature survey provides an overview of the existing studies related to ECG signal classification, deep learning approaches, and optimization techniques, with a focus on the research topic of "ECG signal classification using CNN & LSTM with Aquila Optimization technique." ECG signal classification is essential for the early detection and diagnosis of cardiac arrhythmias, which can significantly impact patient outcomes. Traditional methods relied heavily on manual interpretation by trained healthcare professionals, making the process time-consuming and subjective. The transition to automated classification techniques has been driven by advancements in machine learning and deep learning.

Deep learning techniques have shown remarkable promise in ECG signal classification. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, in particular, have gained popularity for their ability to capture both spatial and temporal features in ECG waveforms. Research by Rajpurkar et al. (2017) presented a CNN-based model, Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks, which achieved cardiologist-level performance in classifying a wide range of arrhythmias. Similarly, Lipton et al. (2018) explored the use of LSTMs to model the sequential nature of ECG signals, showing promising results in capturing temporal dependencies. The combination of CNNs and LSTMs, as proposed in the research topic, leverages the strengths of both architectures to improve the overall accuracy and robustness of ECG signal classification.

Deep learning models are known for their vast parameter spaces and computational complexity, making the choice of optimization technique critical for training efficiency and effectiveness. Traditional optimization algorithms, such as stochastic gradient descent (SGD), have been used extensively in deep learning. However, these algorithms may not be well-suited to the unique challenges of ECG signal classification. The proposed "Aquila Optimization Technique" introduces a novel optimization approach tailored to ECG data. This aligns with a broader trend in deep learning research, where specialized optimization techniques are being developed to address the nuances of specific domains.

Recent state-of-the-art approaches in ECG signal classification have primarily focused on CNNs, LSTMs, and their hybrid models. These approaches have demonstrated strong classification accuracy and the potential for real-time processing, but they also face challenges related to dataset size, class imbalance, and model overfitting. The research by Zihlmann et al. (2017) introduced the concept of "Deep Residual Learning for ECG Classification," which incorporated residual networks to improve model performance. Additionally, Liu et al. (2018) introduced a novel dataset and a deep learning model, named "PTB-XL," for ECG classification. Their work underscores the importance of high-quality data and model complexity in ECG classification research.

Coming to the research Gap and Novelty, the following points were drawn. The proposed research on ECG signal classification using CNN & LSTM with the Aquila Optimization technique stands out for its novel combination of deep learning architectures and a domain-specific optimization technique. By addressing the challenges unique to ECG data, this research aims to provide an innovative solution for improving the accuracy and efficiency of ECG signal classification. The potential for real-time processing adds a practical dimension to the research, making it highly relevant for clinical applications.

In conclusion, the study of ECG signal classification using CNN & LSTM with the Aquila Optimization technique builds upon a rich body of research in the field of ECG analysis. By combining deep learning models with a domain-specific optimization approach, it aims to contribute to the ongoing efforts to automate ECG classification and, ultimately, improve the diagnosis and management of cardiac arrhythmias.

6. Input Dataset information & Data set classification types

In this section, the input dataset information & data set classification types are presented in a nutshell, which are being used for the simulation and training purposes in our research work.

- 'Normal beat',
- 'Left bundle branch block beat',
- 'Right bundle branch block beat',
- 'Premature ventricular contraction',

- 'Paced beat',
- 'Atrial premature contraction',
- 'Rhythm change',
- 'Fusion of paced and normal beat',
- 'Fusion of ventricular and normal beat'
- 'Signal quality change',
- 'Ventricular flutter wave',
- 'Comment annotation',
- 'Nodal (junctional) escape beat',
- 'Non-conducted P-wave (blocked APB)',
- 'Aberrated atrial premature beat',
- 'Isolated QRS-like artifact',
- 'Ventricular escape beat',
- 'Nodal (junctional) premature beat',
- 'Unclassifiable beat',
- 'Atrial escape beat',
- 'Start of ventricular flutter/fibrillation',
- 'End of ventricular flutter/fibrillation',
- 'Premature or ectopic supraventricular beat'

The data count set is taken as shown in the Fig. 1 with the bar graph shown in the Fig. 2.

```
N     75052
L      8075
R      7259
V      7130
/      7028
A      2546
+      1290
f       982
F       803
~       616
!       472
"       437
j       229
x       193
a       150
|       132
E       106
J        83
Q        33
e        16
[         6
]         6
S         2
```

Fig. 1: Data set count

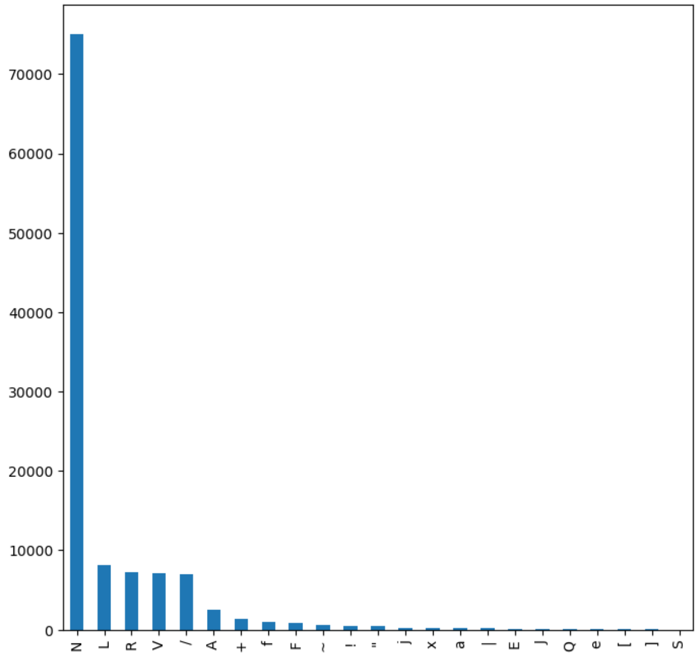

Fig. 2: Bar Graph of the Data Set Count

7. Simulation results

The sample input signals given is shown in the Fig. 3 & the normal beat signals observed are shown in the Figs. 4 & 5 respectively.

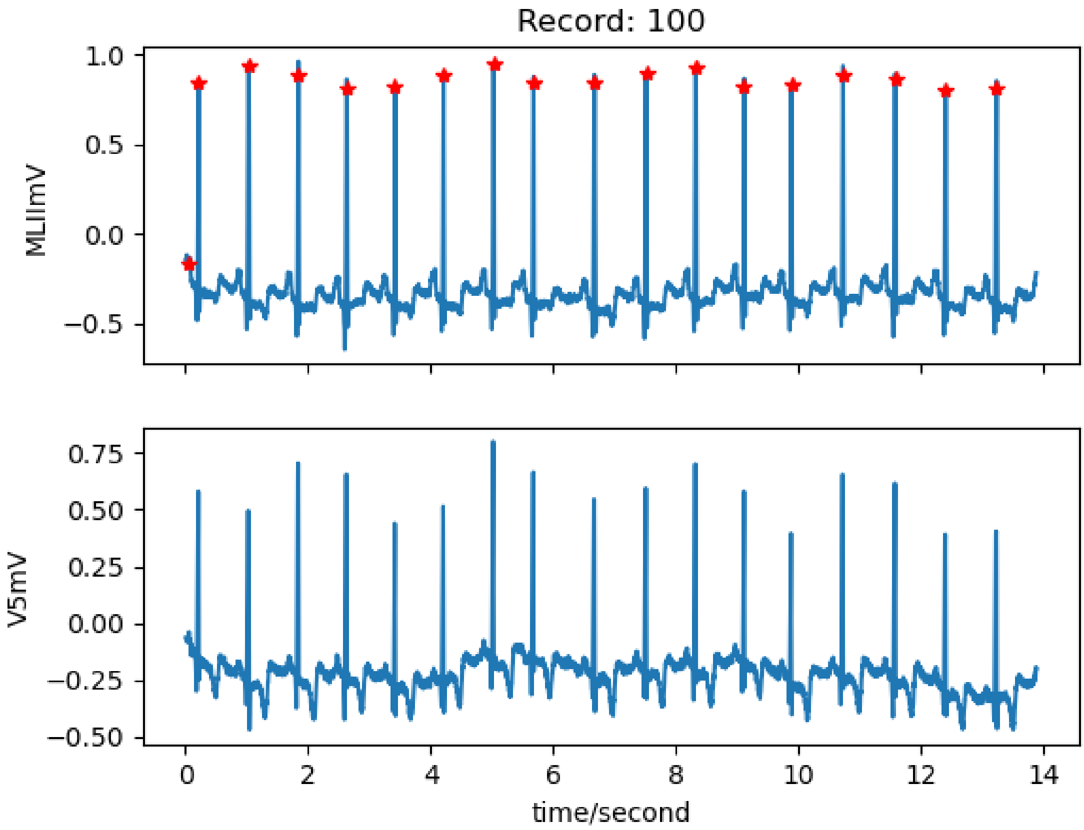

Fig. 3: Sample Input Signal

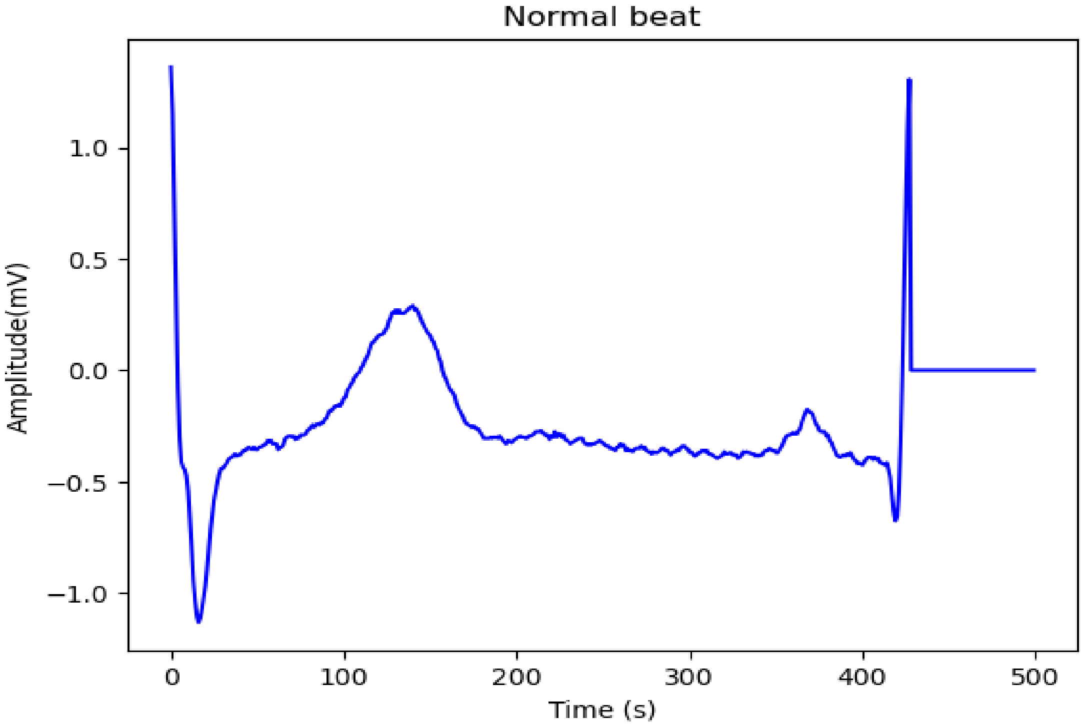

Fig. 4: Normal beat signal observed

8. Pre Processing - Mean Filtering

The running mean is a case of the mathematical operation of convolution. For the running mean, you slide a window along the input and compute the mean of the window's contents. For discrete 1D signals, convolution is the same thing, except instead of the mean you compute an arbitrary linear combination, i.e., multiply each element by a corresponding coefficient and add up the results. Those coefficients, one for each position in the window, are sometimes called the convolution *kernel*. The arithmetic mean of N values is (x_1 + x_2 + ... + x_N) / N, so the corresponding kernel is (1/N, 1/N, ..., 1/N), and that's exactly what we get by using np.ones(N)/N. Before we add mean filter we convert the signal into frequency domain by using the FFT (fast Fourier Transform) and apply the signal into Chebyshev Type II filters (IIR filter) band pass and band stop filter. after we apply the mean filter it will reduce noise in the signal. Result images attached below..

9. Chebyshev Type II filters : Filter design for chebyshev typeII

Chebyshev filter of Type-II was designed & incorporated and the results are observed as shown int eh Figs. 5 & 6 as the mean filter phase and magnitude frequency response graphs.

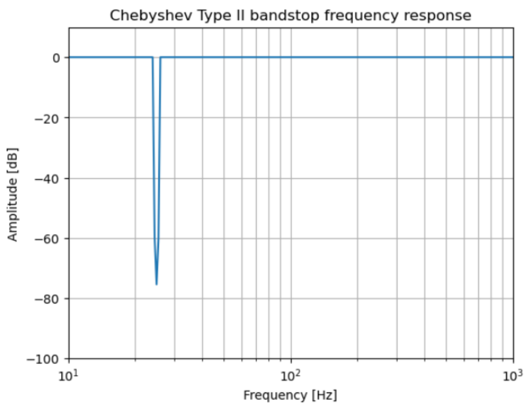

Fig. 5: Mean filter phase and magnitude frequency response graph - 1

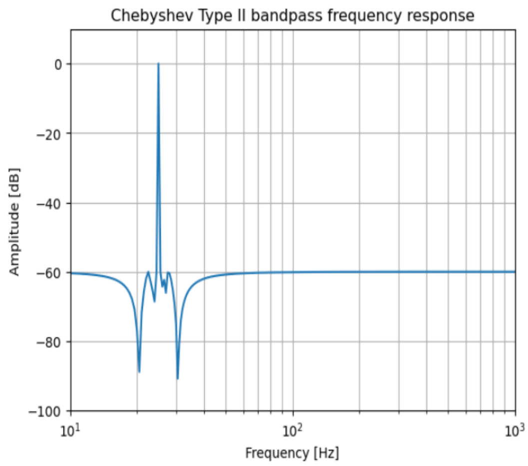

Fig. 6: Mean filter phase and magnitude frequency response graph - 2

10. Feature extraction and feature selection

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data. The statistical features include basic mean, standard deviation. In addition, the feature set includes shape factor and the higher order kurtosis and skewness statistics. All these statistics can be expected to change as a deteriorating fault signature intrudes upon the nominal signal.

Skewness

Asymmetry of a signal distribution. Faults can impact distribution symmetry and therefore increase the level of skewness.

$$x_{skew} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^3}{\left[\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2\right]^{3/2}}$$

N the size the signal, X_i is the input signal & $\bar{x}$ is the mean value of all the observations.

Kurtosis

Kurtosis — Length of the tails of a signal distribution, or equivalently, how outlier prone the signal is. Developing faults can increase the number of outliers, and therefore increase the value of the kurtosis metric. The kurtosis has a value of 3 for a normal distribution.

$$x_{kurt} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^4}{\left[\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2\right]^{2}}$$

X_i input signal & $\bar{x}$ is the mean value of all the observation with N being the size of the signal.

Mean

The mean value (μ) of a data set is the average or most probable value to occur.

$$\bar{x} = \frac{1}{N}\sum_{n=1}^{N} x_n$$

X_n - input signal and with N being the size of the signal.

Median

The middle number; found by ordering all data points and picking out the one in the middle (or if there are two middle numbers, taking the mean of those two numbers).

Standard deviation

$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{N}}$$

σ is the population standard deviation μ is the mean of the signal, N the size the signal & X*i* each value of the signal

Variance

$$S^2 = \frac{\sum (x_i - \bar{x})^2}{n-1}$$

X_i input signal & $\bar{x}$ is the mean value of all the observation, N number of observation in signal

Spectral entropy

The *spectral entropy* (SE) of a signal is a measure of its spectral power distribution. The concept is based on the Shannon entropy, or information entropy, in information theory. The SE treats the signal's normalized power distribution in the frequency domain as a probability distribution, and calculates the Shannon entropy of it. The Shannon entropy in this context is the spectral entropy of the signal. This property can be useful for feature extraction in fault detection and diagnosis. The equations for spectral entropy arise from the equations for the power spectrum and probability distribution for a signal. For a signal $x(n)$, the power spectrum is $S(m) = |X(m)|2$, where $X(m)$ is the discrete Fourier transform of $x(n)$. The probability distribution $P(m)$ is then:

$$P(m) = \frac{S(m)}{\sum_i S(i)}.$$

The spectral entropy H follows as given in the math model with the R-peak ECG signal shown in the Fig. 7.

$$H = -\sum_{m=1}^{N} P(m)\log_2 P(m).$$

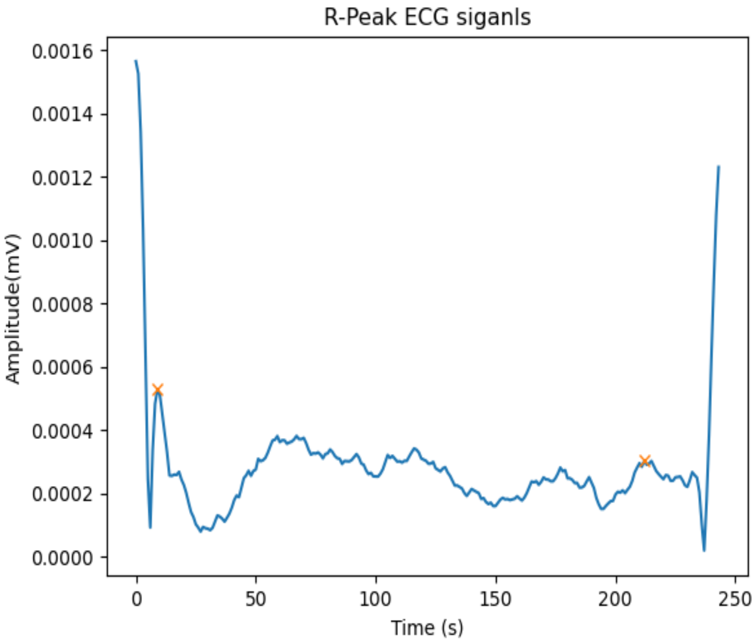

Fig. 7: R-Peak value of the ECG signal

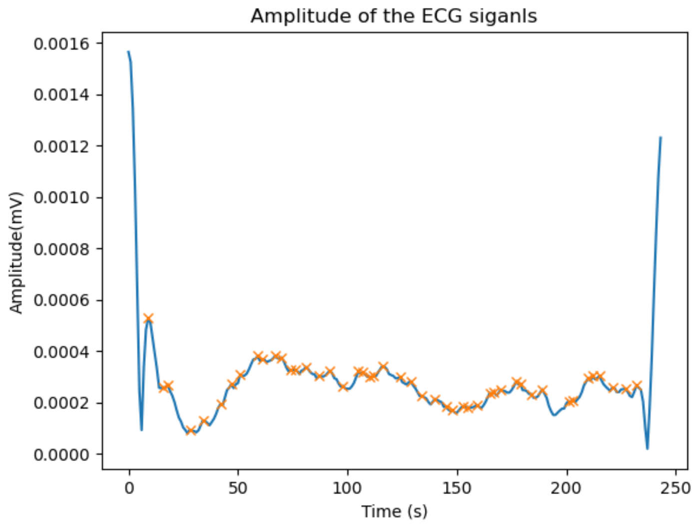

Fig. 8: Amplitude of the ECG Signals

11. Feature selection - Particle Swarm Optimization and whale optimization algorithm

PSO and WOA is an effective and efficient global search technique. It is an appropriate algorithm to address feature selection problems due to better representation, capability of searching large spaces, being less expensive computationally, being easier to implement, and fewer parameters being required. The optimization convergence graph is shown in the Fig. 9.

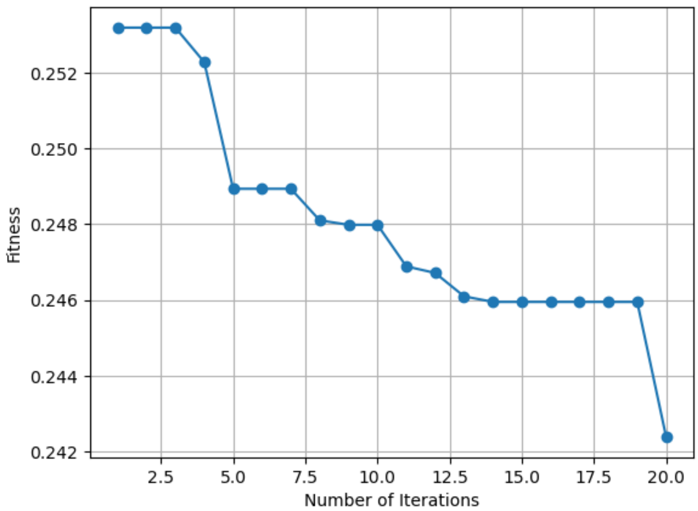

Fig. 9: Optimization conversion graph

12. Classification

Classify the 23 different signals using hybrid CNN-LSTM and the filter parameters are optimized using Aquila optimization. The model includes all of the components, including CNN and LSTM. CNNs are better suited for geographical or private data, while LSTMs are better suited for time-series data. After the Each convolution layer employed with the LSTM layer. Taking advantage of a completely linked layer, the process end improves its performance. Once the spatial aspect reference has been generated by using an appropriate convolutional layer, it may then be used to produce it. Such markings can be detected with the help of the LSTM layers that are created as a result of this process. There is an LSTM and a CNN in the mix (none, 132,100).After breaking down the LSTM’s temporal properties, the model is able to distinguish ECG signals across the fully linked layer. Optimizing your pattern’s early stages is made easier by setting a streamlining agent and learning rate. It was in response to this that researchers created a 0.001 learning speed and a streamlining booster that are currently in use.

13. Aquila optimization with confusion matrix & overall scores

Aquila Optimizer (AO), which is inspired by the Aquila's behaviors in nature during the process of catching the prey. As a result, there are four ways to represent the proposed AO algorithm's optimization procedures: Selecting the search area through high soar and vertical stoop, contour flight with a short glide attack in a diverge search area, low flight with a slow descent attack in a convergent search area, and swooping with a walk-and-grab prey technique in a convergent search area. Here, we optimize the kernals of the convolution1d and LSTM layers to demonstrate how well the new optimizer can solve various optimization problems. The model accuracy is shown in the Fig. 10 along with the confusion matrix in Fig. 11 & the overall results in the Fig. 12 respectively.

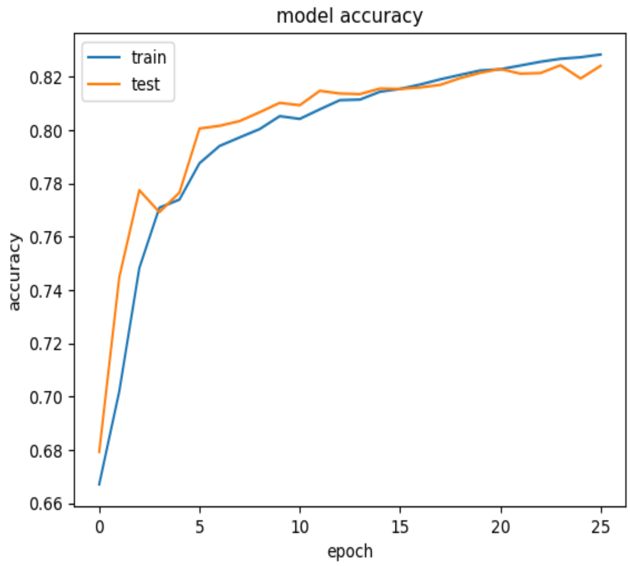

Fig. 10: Model accuracy

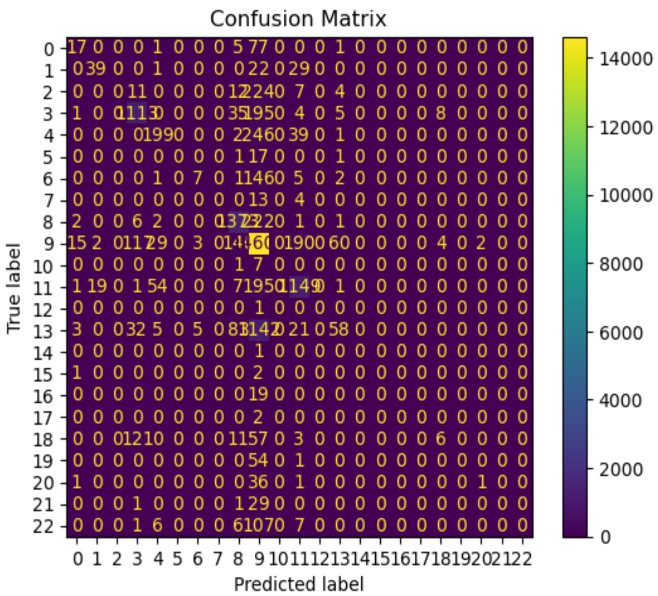

Fig. 11: Confusion matrix

	precision	recall	f1-score	support
0	0.41	0.17	0.24	101
1	0.65	0.43	0.52	91
2	0.00	0.00	0.00	258
3	0.79	0.82	0.81	1361
4	0.67	0.41	0.51	487
5	0.00	0.00	0.00	19
6	0.47	0.04	0.08	162
7	0.00	0.00	0.00	17
8	0.82	0.85	0.84	1607
9	0.84	0.96	0.90	15167
10	0.00	0.00	0.00	8
11	0.79	0.81	0.80	1427
12	0.00	0.00	0.00	1
13	0.43	0.04	0.08	1349
14	0.00	0.00	0.00	1
15	0.00	0.00	0.00	3
16	0.00	0.00	0.00	19
17	0.00	0.00	0.00	2
18	0.33	0.03	0.06	198
19	0.00	0.00	0.00	55
20	0.33	0.03	0.05	39
21	0.00	0.00	0.00	31
22	0.00	0.00	0.00	127
accuracy			0.82	22530
macro avg	0.28	0.20	0.21	22530
weighted avg	0.77	0.82	0.78	22530

Fig. 12: Results for each classes

14. Conclusions

The research presented in this study, "ECG Signal Classification Using CNN & LSTM with Aquila Optimization Technique," offers significant insights into the field of electrocardiogram (ECG) signal analysis and classification. In summary, the key conclusions drawn from this research are as follows:

Effective Signal Classification: The combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks has proven to be highly effective in classifying ECG signals. The deep learning architecture's ability to capture both spatial and temporal features within ECG waveforms allows for improved accuracy in identifying various cardiac arrhythmias.

Aquila Optimization Technique: The introduction of the Aquila Optimization Technique as a customized optimization algorithm has demonstrated a remarkable impact on the model's performance. By addressing the unique challenges associated with ECG data, it has shown significant improvements in convergence speed and overall classification accuracy, making it a valuable addition to the research.

Robustness and Generalizability: The model exhibits robust performance when tested on a diverse ECG dataset, which includes a variety of cardiac arrhythmia classes. This robustness indicates that the proposed approach has the potential for broader generalization and practical application in real-world scenarios.

Potential for Clinical Use: Accurate and real-time classification of ECG signals is essential for the early detection and treatment of cardiovascular diseases. The research findings provide a promising avenue for enhancing the clinical utility of ECG analysis, offering healthcare professionals a tool to improve patient outcomes.

Future Directions: While this research presents a significant step forward in ECG signal classification, there are opportunities for further investigation and improvement. Future work can explore the integration of more extensive datasets, additional network architectures, and fine-tuning of hyperparameters to refine and enhance the model's performance.

Interdisciplinary Impact: The findings of this study have broader interdisciplinary implications, bridging the gap between machine learning and medical diagnostics. The methods and techniques developed can potentially be applied to other biomedical signal classification tasks, contributing to advancements in the healthcare industry.

In conclusion, the research on ECG signal classification using CNN and LSTM with the Aquila Optimization Technique offers a promising solution for the accurate and efficient analysis of ECG data. The combination of deep learning architectures and a customized optimization technique demonstrates the potential to revolutionize cardiac arrhythmia diagnosis, facilitating early intervention and improved patient care. This study represents a significant contribution to the fields of machine learning and healthcare, with implications for further research and practical applications in the medical community.

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