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Recurrent Model for Automatic Detection Cardiac Arrhythmia on the Internet of Healthcare Things

Waleed Abd Elkhalik
Faculty of Computers and Informatics, Zagazig University, Zagazig, Sharqiyah, 44519, Egypt
Email: waleed.abdlekhalik@zu.edu.eg

Abstract

With the growing prevalence of the Internet of Health Things (IoHT), there is an increasing need for reliable and precise categorization of electrocardiogram (ECG) indications for the early detection of cardiovascular diseases. In this research, we propose a machine learning approach for ECG classification in IoHT applications. Our solution use wavelet transforms to clean the ECG records before passing them to the model. Then, a stack of long short-term memory (LSTM) cells is built to learn the temporal interrelations in the ECG signals and make accurate predictions. We assessed the performance of our model on a publicly available dataset of ECG signals, achieving an overall accuracy of 97.5%. The experimental findings demonstrate that our models can effectively classify ECG signals in IoHT applications, providing a valuable tool for the early discovery of vascular diseases. Furthermore, our model can be certainly incorporated into IoHT systems, providing a reliable and efficient solution for ECG classification.

Keywords: Deep Learning; Internet of Healthcare Things (IoHT); ECG classification; Arrhythmia Detection; Smart Healthcare.

1. Introduction

Cardiac arrhythmia is a medical condition characterized by irregular heartbeats or abnormal heart rhythms. This can involve a heart that beats too fast, too slow, or in an irregular pattern. This condition can result in serious health complications, involving heart failure, stroke, and unexpected cardiac mortality. Early detection and intervention are crucial for managing arrhythmias and preventing complications. Arrhythmias can occur in anyone, regardless of age, gender, or health status. Some arrhythmias may be harmless, while others can be life-threatening. Common symptoms of arrhythmias include palpitations (an awareness of the heart beating), dizziness, lightheadedness, fainting, shortness of breath, chest pain, and fatigue. However, some people may not experience any symptoms, and the condition may only be detected during a routine medical check-up or diagnostic test. Arrhythmias can have various underlying causes, including heart infection, high blood force, diabetes, thyroid problems, medications, and lifestyle factors such as stress and alcohol consumption. Treatment for arrhythmias rely on the kind and seriousness of the disorder. Options can range from lifestyle changes, to medication, and medical procedures such as ablation or implantable devices.

An electrocardiogram (ECG or EKG) is an critical acid test that affects the electrical movement of the heart of hearts. It is a non-invasive and painless procedure that requires connecting small rods to the skin on the chest, arms, and legs. The rods identify the electrical signals produced by the heart, which are then recorded as a waveform on a computer or paper strip. An ECG can provide important information about the heart's health and

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function, including the heart rate, rhythm, and presence of any abnormalities. It can help diagnose various heart conditions, such as arrhythmias, heart attacks, and heart disease. ECGs are often used as a screening tool in routine check-ups, as well as in emergency situations to quickly identify and treat potentially life-threatening heart conditions.

Interpreting an ECG requires specialized training and expertise. Healthcare professionals, such as cardiologists or electrophysiologists, analyze the waveforms to determine the heart's health and function. However, manual analysis of ECGs can be laborious and susceptible to faults, particularly for complex arrhythmias. This has led to the development of automated techniques for arrhythmia detection using machine learning, which can analyze large volumes of data quickly and accurately, enabling faster and more reliable diagnosis of arrhythmias.

Machine learning (ML) algorithms have shown great promise in detecting arrhythmias from ECG signals with high accuracy and efficiency. Deep neural networks, support vector machines, and random forests are among the most used ML algorithms for arrhythmia detection. These techniques can analyze large volumes of data quickly and accurately, enabling faster and more reliable diagnosis of arrhythmias. To this end, this paper contributes to the body of knowledge by proposing a supervised deep-learning framework for the efficient detection of Arrhythmia from 12-lead ECG signals. Long short-term memory (LSTM) is stacked in a hierarchical manner to handle the temporal nature of ECG signals, as they are designed to remember long-term dependencies and handle sequential data. This makes them an effective tool for arrhythmia detection, where the timing and duration of electrical signals are crucial.

The structure of this work is planned as follows. Section 2 reviews the recent literature. Section 3 presents a detailed discussion of the methodology of the proposed approach. The design and preparation of our experiments are described in Section 4. Section 5 discusses the experimental findings of this work. finally, Section 6 concludes this study.

2. Related Work

Deep learning (DL) has shown promising results for arrhythmia detection from ECG signals in recent years. Many studies have focused on developing deep-learning models for accurate and efficient arrhythmia classification. For example, the work [1] developed proposed an attention-based time-incremental convolutional model to learn discriminative features from the ECG signals of varying lengths by incrementally processing time-steps of the input signal. The attention layer was adopted to selectively weigh the importance of each time step of the input signal, thereby enabling the model to focus on the most relevant information for arrhythmia detection. The work [2] developed an ML approach that combined feature extraction and classification techniques to accurately detect and classify arrhythmias. The feature extraction process involved computing a set of time-domain and frequency-domain features from the ECG signals, which are then used as input to a support vector machine (SVM) classifier. The work [3] developed a deep multi-scale fusion neural network (DMFN) for multi-class arrhythmia detection, in which three main components were adopted: a multi-scale convolutional neural network (CNN), a fusion module, and a classification module. The multi-scale CNN is designed to extract features from different scales of the input ECG signals, which are then fused together using the fusion module. The work [4] developed an interpretable DL approach for the automatic diagnosis of 12-lead ECG signals, in which a convolutional model was used to learn discriminative features from the ECG signals, and a decision tree-based classifier to make diagnostic decisions based on these features. The work [5] developed a large-scale electrocardiogram (ECG) database that includes data from over 10,000 patients with a variety of arrhythmias. The database was compiled using ECG recordings from patients who had undergone diagnostic testing for arrhythmias at several medical centers in Europe and the United States. The recordings were collected using a standardized protocol that included 12-lead ECGs, and the data were processed to remove noise and artifacts.

More, the work [6] developed a 12-lead ECG arrhythmia detection technique according to a cascaded convolutional model applied to root out arrhythmia features from each single-lead signal. Then, the sequential relationship and longitudinal inconsistency between many advanced, types are flowed as response to two-

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dimensional tightly coupled Residual building units to categorize the arrhythmia. Extracted characteristics according to specialist expertise were passed to the random forest to compute the classification score.

The work [7] developed a DL-based approach that integrated a convolutional model to extract characteristics from the ECG signals, which are also utilized for the classification of different types of myocardial infarction. The proposed approach was evaluated on an open-source data of ECG signals with different types of myocardial infarction, including ST-elevation myocardial infarction (STEMI), non-ST elevation myocardial infarction (NSTEMI), and unstable angina. The work [8] proposed a DL-based methodology for the accurate detection of atrial fibrillation (AF) using 12-lead ECG signals, which are combined convolutional and recurrent layers to learn discriminative features from the ECG signals to detect R-peak and elimination. The work [9] developed a deep convolutional feature extractor to learn representational patterns from long-duration ECG signals, which are then used for the categorization of different types of arrhythmias. The model is composed of multiple convolutional layers with pooling and dropout operations to prevent overfitting. The work [10] applied a bi-directional long short-term memory (LSTM) to learn sequential features from 12-lead ECG signals and classify them into different categories, such as normal sinus rhythm, atrial fibrillation, and other arrhythmias.

3. Methodology

This section discusses the details of building the proposed method for cardiac arrhythmia discovery from ECG signals in IoHT. The proposed methodology for Machine Learning (ML) based Cardiac Arrhythmia detection from ECG in the IoHT involves several steps, including data collection, preprocessing, feature extraction, model development, model evaluation, and deployment. The ECG data is preprocessed to remove noise, artifacts, and baseline wander, and relevant features would be extracted and selected using algorithms.

Noises of various types disrupt any digital signal. Eliminating background noise is a prerequisite for isolating signal characteristics. The equation for a noisy electrocardiogram is:

$$W(t) = S(t) + N(t), \tag{1}$$

The terms $W(t)$ and $S(t)$ denote the ECG signal with and without noise distortion, respectively. In order to clean up an interference-ridden signal, the wavelet transform is frequently used [22]. To remove unwanted ambient noise from the ECG signals, a non-continuous wavelet with the least asymmetric information and a modular carriage is leveraged in our network. The level of specificity applied to each individual case is determined by empirical means. The wavelet transform can be used in three stages to remove noise from an electrocardiogram. Initially, we use the discrete wavelet transform (DWT) of a noisy signal to acquire noisy wavelets. Threshold selection is the second step. In the third step, the signal is cleaned up using an inverse wavelet transform [23]. ECG's DWT is defined as:

$$DWT(a,b) = \frac{1}{\sqrt{2}}\sum_{j=0}^{N} W_j \int_{j}^{j+1} \psi(\frac{t-b}{a})dt, \tag{2}$$

In the above formula, N symbolizes the number of ECG records, W_j denote the noisy ECG time-series with ψ noise. The calculation of DWT involves low-pass as well as high-pass analysis filter to screen, estimate, and compute the DWT coefficients x':

$$y_{low}(t) = \sum_{k=-\infty}^{\infty} W(k)g(2t-k), y_{high}(t) = \sum_{k=-\infty}^{\infty} W(k)h(2t-k). \tag{3}$$

Then, the soft-threshold technique is applied to clear noise from the ECG signal as follows:

$$0 \leq \max(1 - \frac{T}{|x'|}, 0) \leq 1, \tag{4}$$

Followingly, the reverse DWT was applied to obtain the clean edition of ECG records:

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$$S(t) = \sum_{k=-\infty}^{\infty} \tilde{g}_k y_{low_k}(t) + \sum_{m=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} \tilde{h}_{m_k} y_{high_k}(t), \tag{5}$$

By doing the above steps, we have completed the ECG engineering steps, and the ECG data now are ready to be segmented into windows and normalized according to the following steps.

$$f(x) = x * c - (x_m * c) + m \; with \; c = (\frac{ub - lb}{x_{\max} - x_{\min}}) \tag{6}$$

In which, x_m is the middle point of input, and is computed as:

$$x_{mid} = x_{\max} - \frac{x_{\max} - x_{\min}}{2}, m = ub - \frac{ub - lb}{2} \tag{7}$$

The ML classifier is implemented using LSTM trained on the selected features, and the trained model would be evaluated using a separate test dataset. Once the LSTM is developed and evaluated, it would be deployed in the IoHT environment for real-time arrhythmia detection. The proposed methodology could lead to an accurate and automated system for detecting cardiac arrhythmias in real time, enabling early intervention and improved patient outcomes. ECG classification is a crucial task in detecting various heart diseases such as arrhythmias, myocardial infarction, and heart failure. Due to the complex and dynamic nature of ECG signals, traditional classification methods often fail to provide satisfactory results. LSTM networks have emerged as a powerful tool for ECG classification, capable of modeling long-term dependencies and effectively capturing the temporal dynamics of the cleaned ECG signals. LSTMs can learn to recognize patterns in the denoised ECG signals and classify them into different categories based on the learned features, allowing for the accurate detection of heart diseases. The

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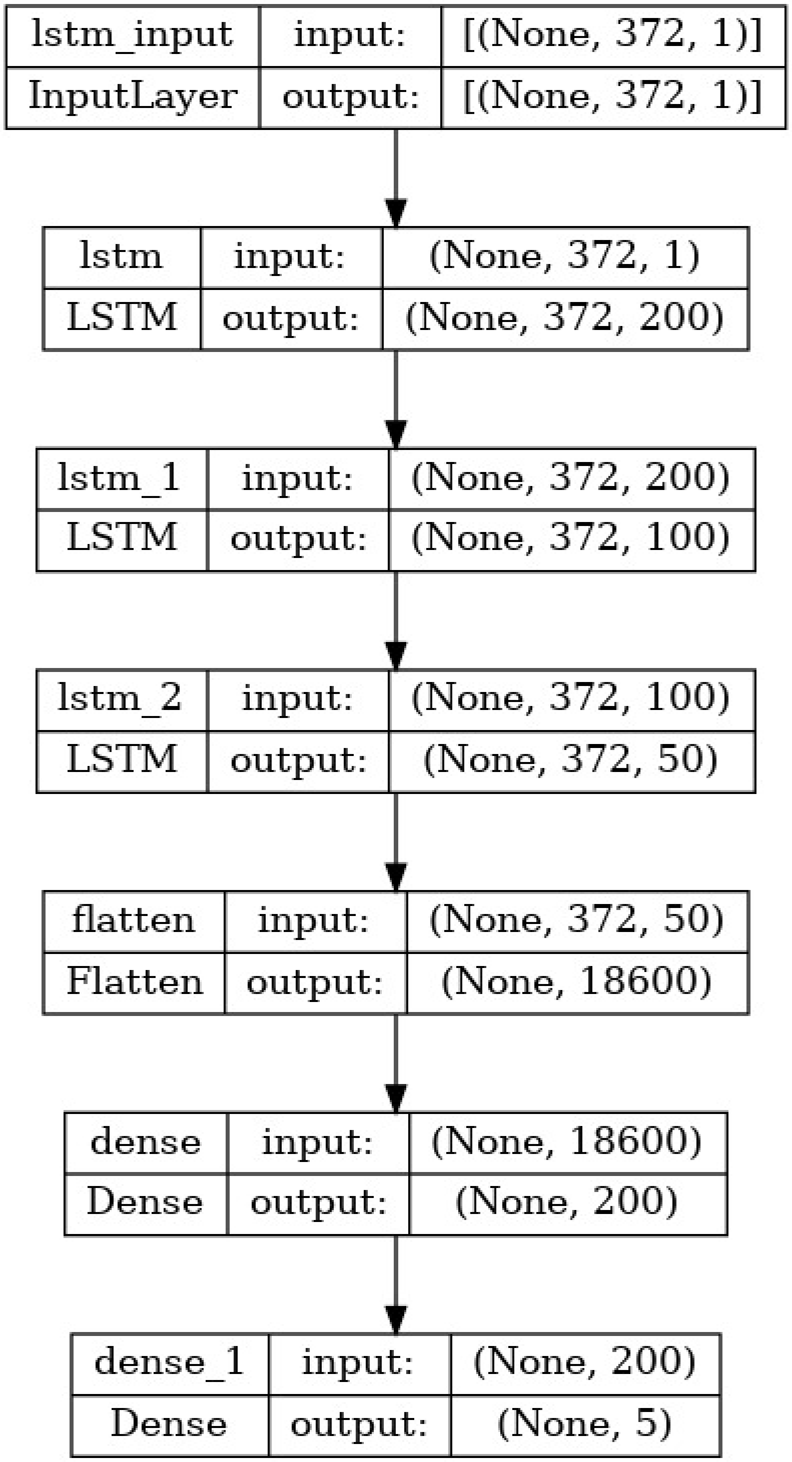

Figure 1. Visualization of the architecture of the proposed model.

cleaned ECG signals are fed into the LSTM model composed of multiple LSTM layers (See Figure 1). The LSTM process receives cleaned ECG signals through the following gating computations:

$$\text{input gate} \rightarrow \; i_t = \sigma(W_i([x_t, y_{t-1}])) \qquad (8)$$

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$$\text{forget gate} \rightarrow f_t = \sigma(W_f([x_t, y_{t-1}])) \tag{9}$$

$$\text{output gate} \rightarrow o_t = \sigma(W_o([x_t, y_{t-1}])) \tag{10}$$

$$g_t = tanh(W_g([x_t, y_{t-1}])) \tag{11}$$

$$\text{input update} \rightarrow c_t = f \odot c_{t-1} + i \odot g \tag{12}$$

$$y_t = o \odot tanh(c_t) \tag{13}$$

One of the key advantages of using LSTM networks for ECG classification is their ability to handle varying input sequence lengths. ECG signals are usually of varying lengths, and traditional machine-learning models struggle to handle this variability. However, LSTMs can effectively handle variable-length input sequences by processing them sequentially, allowing them to learn from the entire sequence of ECG signals. This feature of LSTMs makes them particularly useful for real-time ECG classification and monitoring applications, as they can process incoming ECG signals continuously and provide accurate predictions in real time.

4. Experimental Setup

In this section, we debate the main installations and preparation made to conduct experiments of this work. In particular, the following subsection debate the dataset description, the environmental setup, the evaluation indicators, and the hyper-parameters.

4.1. Dataset Description

The experiments of this study used the MIT-BIH Arrhythmia dataset to train and evaluate the DL models. The MIT-BIH data comprises 48 half-hour pieces of two-channel ambulant ECG records, taken from 47 individuals examined between 1975 and 1979 at the BIH Arrhythmia Lab. A sample of 23 records was arbitrarily selected from a group of 4000 daily ambulant ECG tapes recorded from a mixture of inpatients and outpatients at Boston's Beth Israel medical center. The leftover 25 records were also carefully chosen from the abovementioned populations to incorporate less popular yet medically considerable arrhythmias that would not be well-characterized in a tiny arbitrary sample. In MIT-BIH data, the ECG records were digitalized at 360 trials per second by 11-bit resolution across a 10-mV scale. The annotation of ECG records was independently performed with more than two cardiologists annotating each record; in which the conflicts were solved to attain the computerized source annotations for each knock contained in the dataset. In our experiments, we rename the classes as follows. Class 0.: 'Normal Beat', class 1. : 'Supraventricular premature beat', Class 2. : 'Premature ventricular contraction', class 3. : 'Fusion of ventricular', class 4. : 'Unclassifiable beat'. Table 1 summarize the statistics of some attributes of MIT-BIH data comprises.

Table 1: summary of statistics of each variable in MIT-BIH data

Attribute	count	mean	std	min	25%	50%	75%	max
0	87554	0.89036	0.240909	0	0.921922	0.991342	1	1
1	87554	0.75816	0.221813	0	0.682486	0.826013	0.910506	1

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2	87554	0.423972	0.227305	0	0.250969	0.429472	0.578767	1
3	87554	0.219104	0.206878	0	0.048458	0.166	0.341727	1
4	87554	0.201127	0.177058	0	0.082329	0.147878	0.258993	1
5	87554	0.210399	0.171909	0	0.088416	0.158798	0.287628	1
6	87554	0.205808	0.178481	0	0.073333	0.145324	0.298237	1
7	87554	0.201773	0.17724	0	0.066116	0.144424	0.295391	1
8	87554	0.198691	0.171778	0	0.065	0.15	0.290832	1
9	87554	0.196757	0.168357	0	0.068639	0.148734	0.283636	1
10	87554	0.198778	0.171796	0	0.070543	0.145985	0.287781	1
11	87554	0.20355	0.176496	0	0.069182	0.14859	0.293367	1
12	87554	0.208776	0.180274	0	0.068293	0.152951	0.303079	1
13	87554	0.212885	0.184101	0	0.067744	0.156863	0.310992	1
14	87554	0.218393	0.186963	0	0.070175	0.162636	0.316505	1
15	87554	0.224966	0.190002	0	0.072993	0.169399	0.321809	1
...	...	...	...	...	...	...	...	...
175	87554	0.006531	0.05284	0	0	0	0	1
176	87554	0.005981	0.050006	0	0	0	0	1
177	87554	0.005479	0.046693	0	0	0	0	1

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178	87554	0.005025	0.044154	0	0	0	0	1
179	87554	0.004628	0.042089	0	0	0	0	1
180	87554	0.004291	0.040525	0	0	0	0	1
181	87554	0.003945	0.038651	0	0	0	0	1
182	87554	0.003681	0.037193	0	0	0	0	1
183	87554	0.003471	0.036255	0	0	0	0	1
184	87554	0.003221	0.034789	0	0	0	0	1
185	87554	0.002945	0.032865	0	0	0	0	1
186	87554	0.002807	0.031924	0	0	0	0	1
187	87554	0.473376	1.143184	0	0	0	0	4

4.2. Environmental setup

The design of all experiments is performed in a python 3.9 environment, in which TensorFlow 2.60 is used to implement, train, and evaluate the deep learning models. All these setups are performed on the Dell Workstation equipped with 64 RAM, Nvidia P100 GPU, and Intel(R) Xeon (TM) CPU 3.20GHz CPU and operated with Windows 10 operating system.

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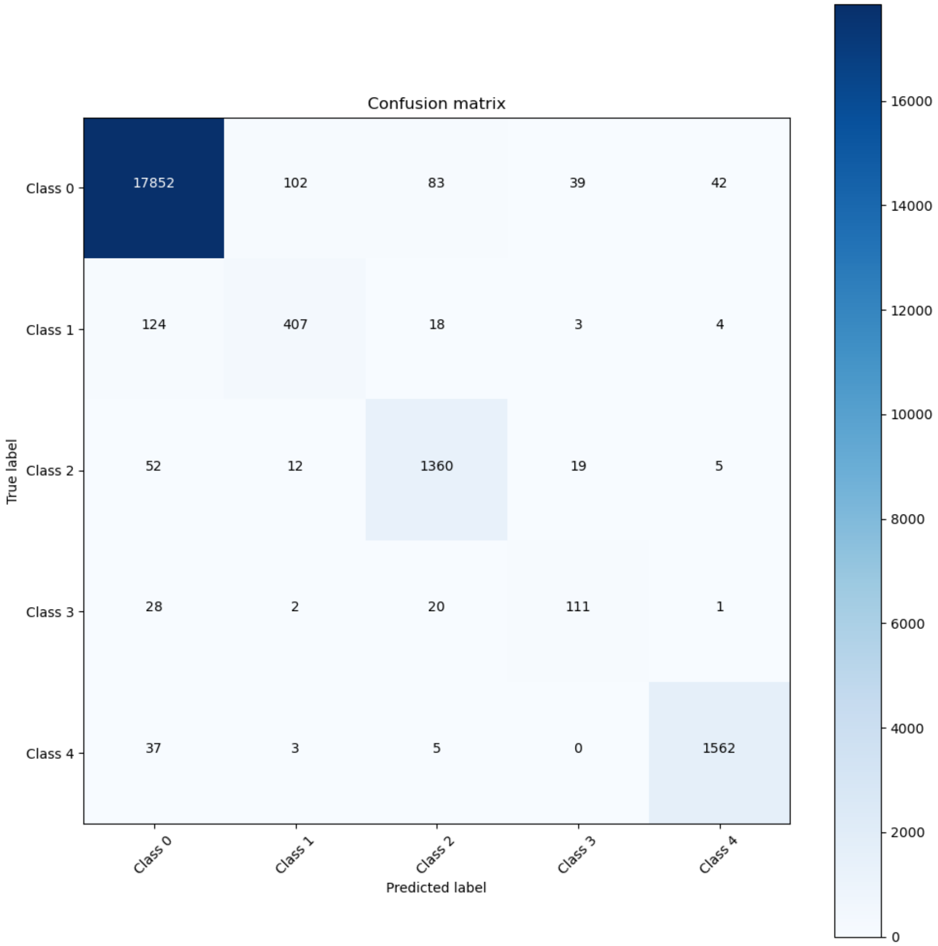

Figure 2. visualization of confusion matrix plot for the proposed model

4.3. Evaluation Indicators

To assess the performance of the planned methodology, this section debates the performance indicators adopted in our experiments. A confusion matrix is a common evaluation indicator that has been broadly used in the classification task, hence, it is adopted as the essential indicator in our experiments. More, the accuracy and f1-measure, are also common indicator calculated based on the confusion matrix as follow:

$$Accuracy\ (A) = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{14}$$

$$F1 - score\ (F1) = \frac{2TP}{2TP + FP + FN} \times 100, \tag{15}$$

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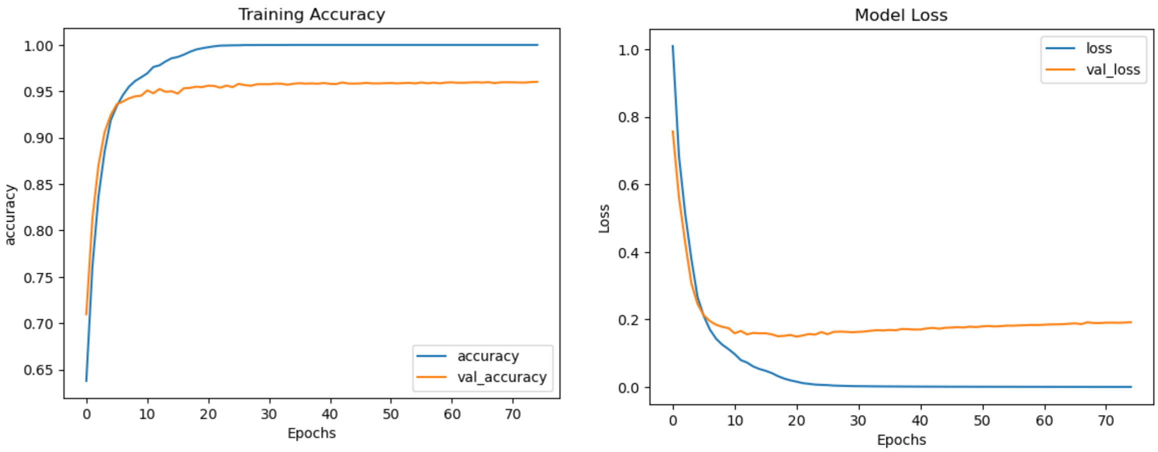

Figure 3: visualization of training curves for the proposed model

5. Results and Discussion

This piece offers a conclusive analysis of the empirical findings obtained from the proposed approach. A detailed discussion of each conducted experiment is provided in the following section. A confusion matrix is a commonly used tool to evaluate the performance of a classification model. It provides a summary of the number of correct and incorrect predictions made by the model on a set of test data. In the context of ECG classification, a confusion matrix is displayed in Figure 2 to evaluate the performance of a model in correctly classifying ECG signals into different categories (e.g., normal, arrhythmic). Given the visualized values, several metrics can be computed to assess the performance of the ECG classification model, such as accuracy (97.26%), recall (86.27%), precision (85.77%), and f1-measure (85.99%).

Training curves are a graphical interpretation of the learning progress of a machine learning model during the training process. In the context of ECG classification, training curves can be used to monitor the performance of our model on the training and validation datasets as the training progresses (see Figure 3). As shown, the used training curves for ECG classification are the loss curve and the accuracy curve. The loss curve shows how the training and validation loss change over the course of training. A decreasing loss curve indicates that the model is learning to make better classifications. The accuracy curve shows how the training and validation accuracy

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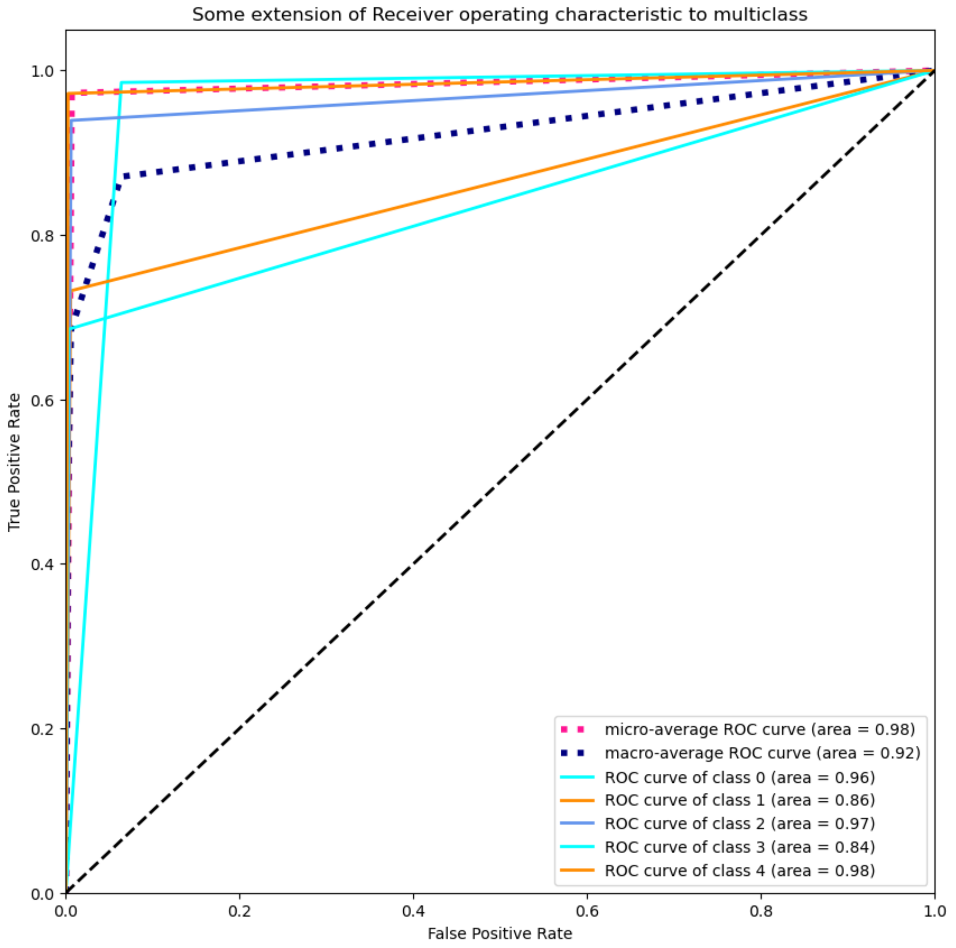

Figure 4: visualization of ROCAUC curves for the proposed model

change over the course of training. An increasing accuracy curve indicates that the model is improving in its ability to correctly classify ECG signals. as shown, the proposed model is able to capture the full complexity of the ECG signals and is, therefore, able to generalize well to new data.

A Receiver Operating Characteristic (ROC) curve is a graphic interpretation of the presentation of classification model (i.e., a model that classifies ECG signals into two categories, such as normal or arrhythmic). In the context of ECG classification, a ROC curve is applied to assess the sensitivity and specificity of the model at different classification thresholds (see Figure 4). The area under the ROC curve (AUC) provides a summary of the overall performance of the ECG classification model, with a higher AUC indicating superior execution. By adjusting the classification threshold, it is possible to trade off the TPR and FPR, depending on the specific requirements of the application. For example, in a clinical setting, it may be more valuable to reduce false negatives (i.e., arrhythmic ECG signals that are incorrectly identified as normal) than false positives (i.e., normal ECG signals that are incorrectly identified as arrhythmic). The ROC curve and AUC is utilized to assess the performance of the ECG classification model under different trade-off scenarios and to select the optimal classification threshold for a given application.

6. Conclusion

In brief, this work presents a deep learning methodology for real-time detection the Arrhythmia for 12-lead ECG signals in IoHT. LSTM networks have demonstrated encouraging outcomes for arrhythmia detection. Arrhythmia is a medical disorder that affects the heart's rhythm, and early exposure can lead to better treatment

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outcomes. LSTM models have been trained on electrocardiogram data and have shown high accuracy in detecting different types of arrhythmias. By analyzing the patterns and features of ECG signals, LSTM models can learn to identify abnormal heart rhythms with high accuracy. Moreover, LSTM models can handle the temporal nature of ECG signals, as they are designed to remember long-term dependencies and handle sequential data. This makes them an effective tool for arrhythmia detection, where the timing and duration of electrical signals are crucial. Exhaustive experimentations on public datasets validate the proficiency of the proposed methodology by surpassing the state-of-the-art methods under fair comparisons. The stability and efficiency of our solution make it a suitable candidate to be deployed as a reliable tool for ECG analysis in sustainable healthcare.

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