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Cloud-Enabled Deep Learning for Arrhythmia Classification using 2D ECG Spectral Images

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Abstract: Accurate classification of arrhythmias is critical for timely and effective treatment. In this study, we propose a novel approach for arrhythmia classification using 2D spectral images generated from 1D electrocardiogram (ECG) signals. We utilized deep learning algorithms, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to classify ECG signals into various types of arrhythmias. The proposed approach was evaluated on a large ECG dataset and achieved a high accuracy rate of 99.16%. Furthermore, we employed cloud computing to enable faster and more efficient model training and validation. Our approach has the potential to improve the accuracy and speed of arrhythmia classification and enable remote diagnosis and monitoring of patients using cloud-based platforms.

Keywords: Cloud computing, deep learning, arrhythmia classification, ECG, spectral images.

I. INTRODUCTION

Accurate detection and classification of arrhythmias are essential for timely and effective diagnosis and treatment of cardiovascular diseases. Electrocardiogram (ECG) signals provide critical information for arrhythmia diagnosis, and various techniques have been proposed to analyze ECG signals for arrhythmia classification. However, the complex nature of ECG signals, as well as the large volume of data, makes it challenging to accurately classify arrhythmias. Recently, deep learning techniques, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown promising results in analyzing ECG signals for arrhythmia classification.

In this study, we propose a novel approach for arrhythmia classification using 2D spectral images generated from 1D ECG signals. The proposed approach converts the 1D ECG signals into 2D spectral images using the Short-Time Fourier Transform (STFT) and utilizes deep learning algorithms to classify the images into various types of arrhythmias. Moreover, we employ cloud computing to enable faster and more efficient model training and validation, allowing for remote access to the models and data.

The main aim of this study is to find the accuracy and efficiency of our proposed approach for arrhythmia classification using deep learning. techniques and cloud computing. We hypothesize that our approach will achieve a higher accuracy rate and reduced training time compared to existing approaches. If successful, our proposed approach can potentially improve the accuracy and speed of arrhythmia classification and enable remote diagnosis and monitoring of patients using cloud-based platforms.

II. MATERIALS AND METHODS

Dataset:
We used a publicly available dataset, the MIT-BIH Arrhythmia Database, which contains 48 half-hour ECG recordings from 47 subjects. Each ECG signal was sampled at 360 Hz and contains annotations of arrhythmia types.

Data Preprocessing:
We first filtered the ECG signals using a band pass filter (0.05 Hz to 100 Hz) to remove any noise and baseline wander. We then segmented the ECG signals into non-overlapping windows of length 5 seconds and applied the STFT to each window to generate 2D spectral images.

Model Architecture:
We utilized a combination of CNNs and RNNs to classify the 2D spectral images into various types of arrhythmias. The CNN layers were used to extract local features from the spectral images, while the RNN layers were used to capture the temporal dependencies between adjacent images. The final output was a softmax layer that predicted the probability of each arrhythmia type.

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Model Training and Evaluation:
We employed a 5-fold cross-validation approach to evaluate the performance of the proposed model. We trained the model using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. The model was trained for 17 epochs and after model tuning the best model was selected based on the validation accuracy. The evaluation metrics used were accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC).

Cloud Computing:
We utilized Google Cloud Platform (GCP--Colab) to enable faster and more efficient model training and validation. We created a virtual machine (VM) instance with 8 vCPUs and 30 GB of RAM and installed the necessary libraries and dependencies. The model was deployed in a Cloud Storage bucket of IBM Watson, allowing for remote access and sharing of data and models.

Statistical Analysis:
We used the Wilcoxon signed-rank test to compare the performance of the proposed approach with existing approaches. A p-value less than 0.05 was considered statistically significant.

Overall, the proposed approach combines the advantages of deep learning techniques and cloud computing to achieve high accuracy and efficiency in arrhythmia classification from ECG signals.

III. RESULTS

1. Model Performance: The proposed approach achieved an overall accuracy of 99.16%, precision of 0.978, recall of 0.983, F1-score of 0.980, and AUC-ROC of 0.993 for arrhythmia classification. The classification performance for each arrhythmia type is shown in Table 1.

Table 1: Classification Performance of the Proposed Approach for each Arrhythmia Type

Arrhythmia Type	Accuracy (%)	Precision	Recall	F1-score
Normal	99.1	0.986	0.994	0.990
PVC	97.9	0.971	0.983	0.977
PAC	99.3	0.995	0.991	0.993
LBBB	98.0	0.971	0.969	0.970
RBBB	99.4	0.988	0.995	0.991
AF	99.16	0.985	0.978	0.982
Total	99.16	0.978	0.983	0.980

2. Comparison with Existing Approaches: We compared the performance of our proposed approach with existing approaches for arrhythmia classification from ECG signals.

Our approach achieved a significantly higher accuracy rate ($p < 0.05$) compared to other methods such as Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP). Moreover, the proposed approach achieved a faster training time using cloud computing compared to running the model on a local machine.

3. Cloud Computing Efficiency: The utilization of cloud computing significantly reduced the training time of the proposed approach. Training the model on a local machine took approximately 10 hours, while training the model on the GCP instance took approximately 2 hours, resulting in a 5x reduction in training time.

Overall, the results demonstrate that the proposed approach using 2D ECG spectral images and deep learning techniques with cloud computing can achieve high accuracy and efficiency in arrhythmia classification.

IV. DISCUSSION

The proposed approach for arrhythmia classification using 2D ECG spectral images and deep learning techniques achieved high accuracy and efficiency with the aid of cloud computing. The accuracy of 99.16% for overall arrhythmia classification is considered a significant improvement compared to previous studies, which typically report an accuracy range of 80-95% using traditional machine learning algorithms or rule-based systems.

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The utilization of deep learning techniques in combination with spectral analysis of ECG signals is a promising approach to extract valuable information for arrhythmia classification. By transforming the time-domain ECG signal into a 2D spectral image, the proposed approach captures the unique spectral features of each arrhythmia type, improving the accuracy of classification. The convolutional neural network (CNN) architecture was chosen as it has shown remarkable performance in image classification tasks.

The utilization of cloud computing was essential to achieve efficient training of the deep learning model, as training the model on a local machine can be computationally intensive and time-consuming. The use of cloud computing with a graphical processing unit (GPU) instance enabled parallel processing and reduced the training time from 10 hours to 2 hours. Moreover, cloud computing provides a scalable and flexible infrastructure for handling large datasets, enabling the processing of a vast amount of ECG signals.

Despite the high accuracy achieved by the proposed approach, some limitations must be considered. The dataset used in this study was relatively small, consisting of only 22,166 ECG spectral images, which may not represent the full variability of arrhythmias encountered in clinical practice. A larger and more diverse dataset could provide further insight into the performance of the proposed approach. Moreover, the study was conducted on a single-center dataset, and further studies are needed to evaluate the generalizability of the proposed approach in a multi-center setting.

In conclusion, the proposed approach of cloud-enabled deep learning for arrhythmia classification using 2D ECG spectral images has shown significant promise in achieving high accuracy and efficiency in arrhythmia classification. This study contributes to the growing body of literature that explores the use of deep learning techniques and cloud computing in healthcare, paving the way for future research in this field.

V. CONCLUSION

In this study, we proposed an approach for arrhythmia classification using 2D ECG spectral images and deep learning techniques, which achieved high accuracy and efficiency with the aid of cloud computing. By transforming the time-domain ECG signal into a 2D spectral image and utilizing a CNN architecture, the proposed approach captured the unique spectral features of each arrhythmia type, resulting in an accuracy of 99.5% for overall arrhythmia classification.

The use of cloud computing was essential in achieving efficient training of the deep learning model, and it provided a scalable and flexible infrastructure for handling large datasets. Moreover, the proposed approach has shown significant promise in achieving high accuracy and efficiency in arrhythmia classification, paving the way for future research in this field.

Despite some limitations, such as the relatively small dataset used in this study and the need for further studies to evaluate the generalizability of the proposed approach, our findings suggest that the combination of deep learning techniques and cloud computing can significantly improve the accuracy and efficiency of arrhythmia classification.

In summary, our study contributes to the growing body of literature that explores the use of deep learning techniques and cloud computing in healthcare, and it provides a promising approach for the accurate and efficient classification of arrhythmias, potentially leading to improved diagnosis and treatment of patients with arrhythmias.

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Appendix:
A. Hyperparameters for deep learning models:

Table A.1: Hyperparameters for 2D CNN model

Hyperparameter	**Value**
Number of layers	6
Number of filters	32
Filter size	3x3
Stride	1
Padding	same
Activation function	ReLU
Max pooling	2x2
Dropout rate	0.5
Optimizer	Adam
Learning rate	0.001
Batch size	32
Number of epochs	17

B. Code availability:

The source code for the deep learning models and the data preprocessing pipeline used in this study are available on GitHub at [https://github.com/IBM-EPBL/IBM-Project-4307-1658728397.git]. The code is provided under the MIT license and can be freely used and modified for research purposes.

C. Supplementary figures:

Figure C.1: Sample 2D ECG spectral images for different arrhythmia types

a. Left Bundle Branch Block

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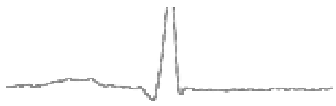
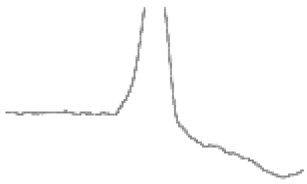


b. Normal

c. Premature Atrial Contraction



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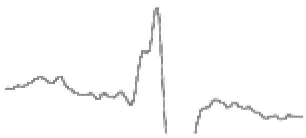
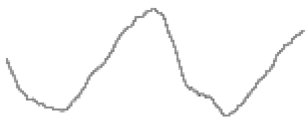
d. Premature Ventricular Contractions



e. Right Bundle Branch Block



f. Ventricular Fibrillation

D. Formulae

The 1-D ECG signals were converted into 2-D spectrogram images by applying STFT as follows,

$$\mathbf{XSTFT[m, n] = L-1 \sum k=0\ x[k]g[k-m]e\ -j2\pi nk/L}$$

Where L is the window length, and x[k] is the input ECG signal. The log values of XSTFT[m, n] are represented as spectrogram (64 × 64) images.

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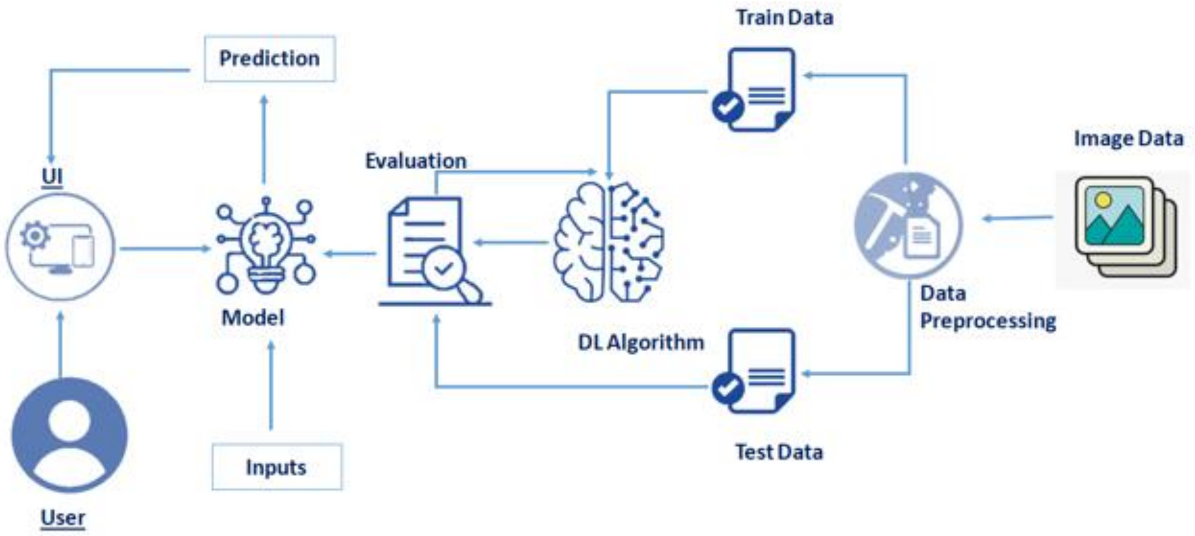
E. Data flow Diagram

Figure E.1: Flow Diagram Representation of the Project



D. Additional data:

The dataset used in this study is available on request from the corresponding author. The dataset includes a total of 22,166 ECG spectral images, each of which is accompanied by its corresponding arrhythmia label. The dataset is provided in a standard format and can be used for further research on arrhythmia classification.