Project # 23

ECG Interpretation with Machine Learning

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Overview

Electrocardiograms (ECGs) are critical diagnostic tools for assessing heart conditions, such as arrhythmias and myocardial infarctions. However, manual ECG interpretation is subject to interobserver variability and human error, making it essential to explore automated methods. This project integrates Convolutional Neural Networks (CNNs) with ECG analysis, offering a more reliable and efficient alternative for accurate diagnostics.

The objectives of this project are:

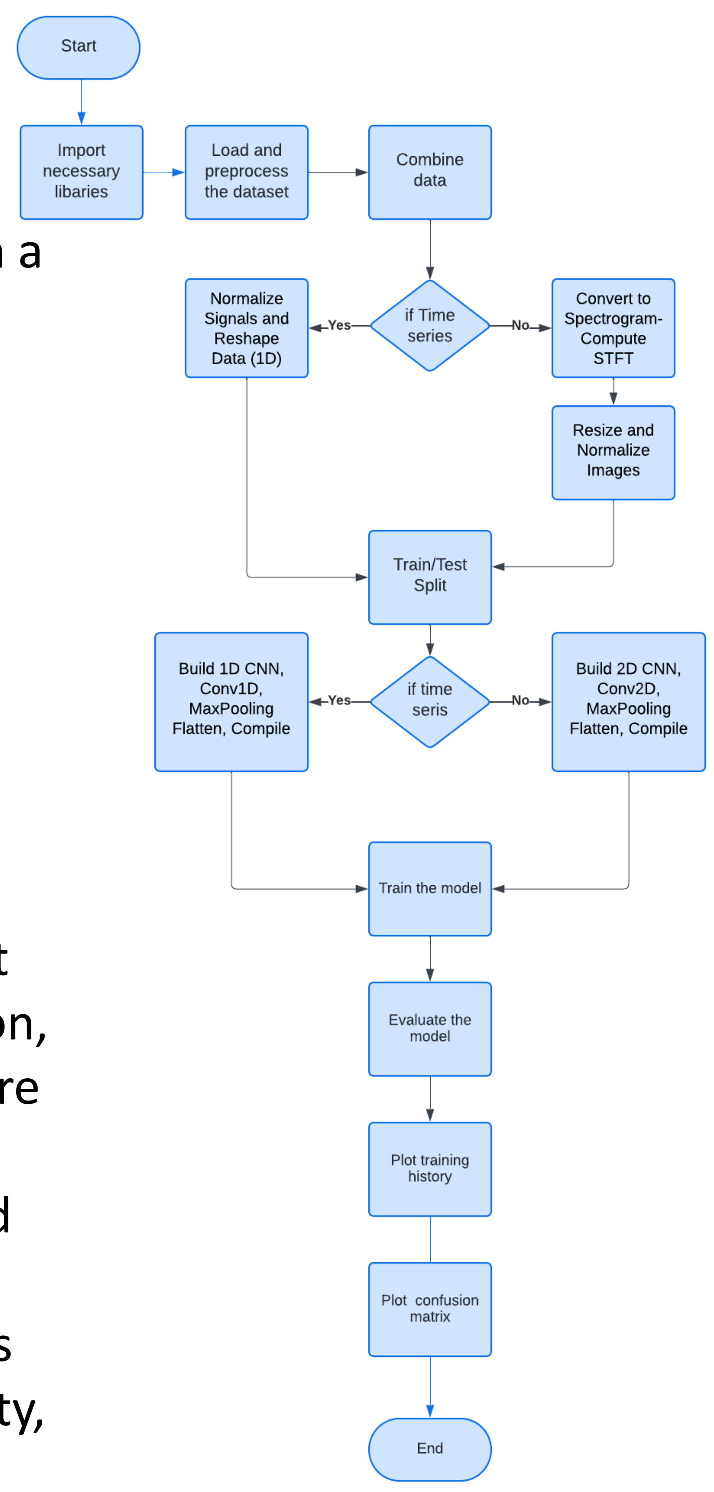
- Extract key ECG features for better classification.
- Use CNNs to automate the analysis of ECG signals, transforming them into spectrograms to improve pattern recognition and classification accuracy.

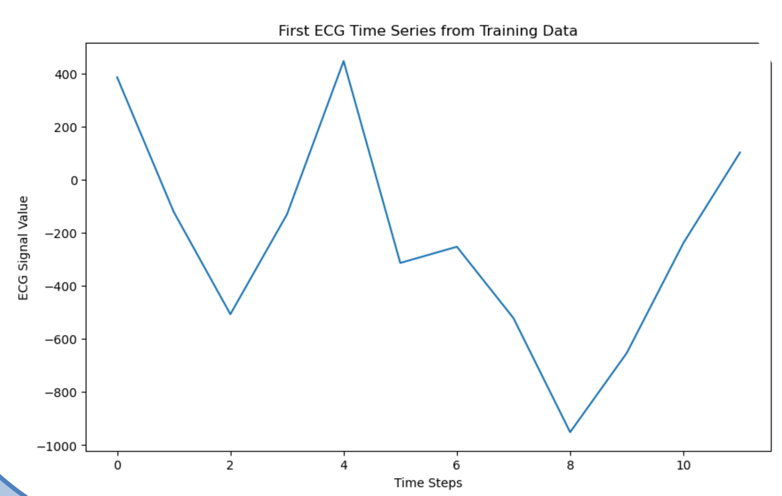
Previous work/Literature review

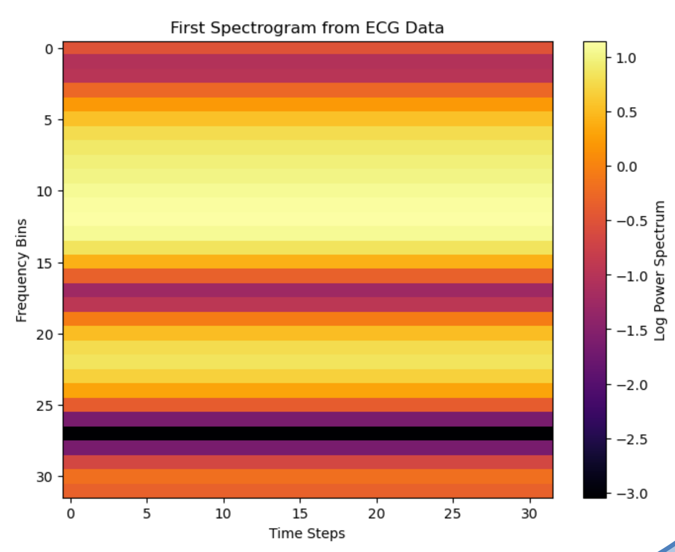
In ECG interpretation, significant advancements have been made using Convolutional Neural Networks (CNNs) for signal classification. [1] Indolia et al. highlighted the effectiveness of CNN architectures in medical signal processing, while [2] Semenoglo et al. introduced a method that transforms time series data into images, achieving improved forecasting accuracy. My work differentiates itself by focusing on ECG data with a 1D CNN model specifically designed for binary classification of ECG traces. It employs a novel preprocessing technique that converts time series data into images to enhance feature representation and utilizes a labeled ECG dataset, ultimately aiming for real-time classification to improve patient management.

Methodology

1. Data Preprocessing: ECG signals (lead I) are filtered, normalized, and reshaped into 3D arrays for CNN input. Spectrograms are created using STFT at 250 Hz with a 128-segment length.
2. Feature Extraction: Signals are segmented into 5000-sample windows, and spectrograms are generated to enhance feature extraction.
3. Model Development: A 1D CNN with convolution, pooling, and dropout layers is implemented using TensorFlow and Keras.
4. Training & Validation: The dataset is split into 80% training, validation, and test sets. Hyperparameters are optimized, and performance is evaluated with accuracy, loss, and precision.
5. Evaluation: Model effectiveness is assessed using accuracy, sensitivity, precision, and a confusion matrix to classify normal vs. abnormal ECG rhythms.

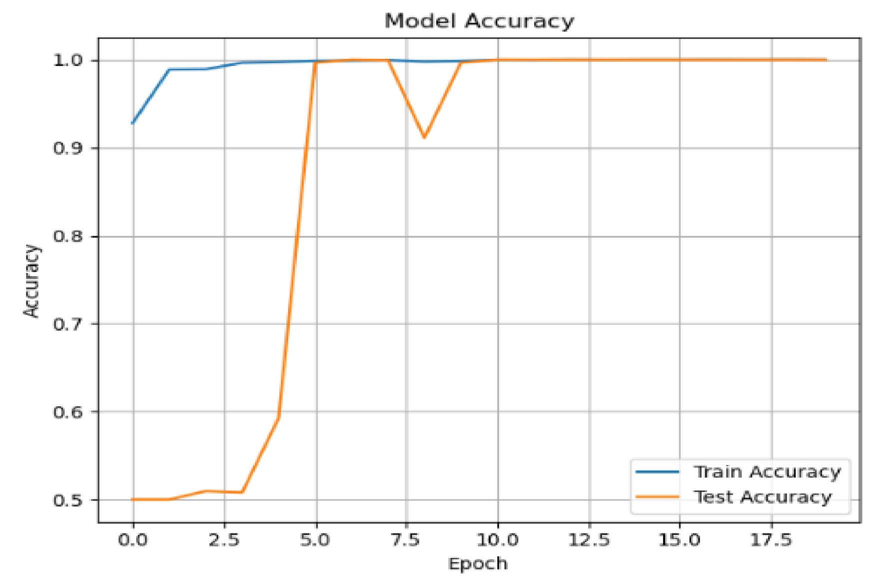


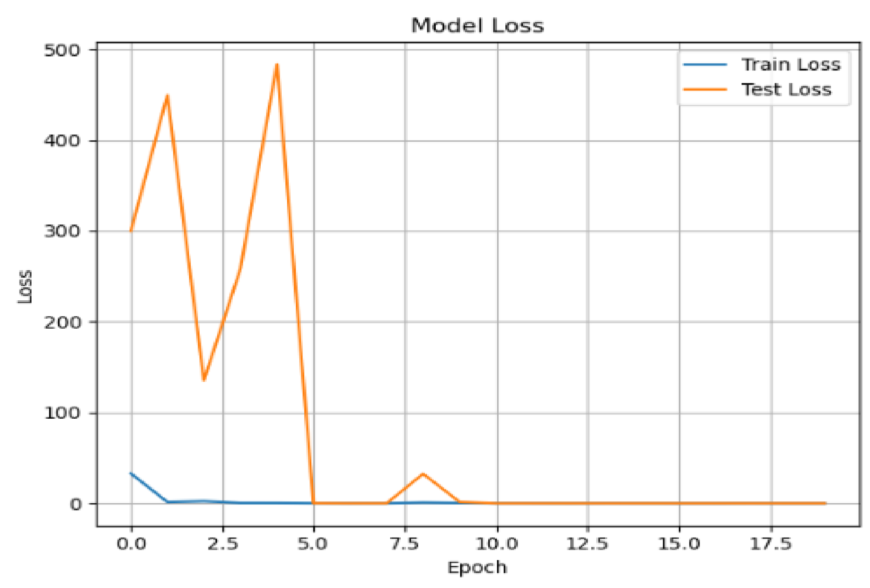


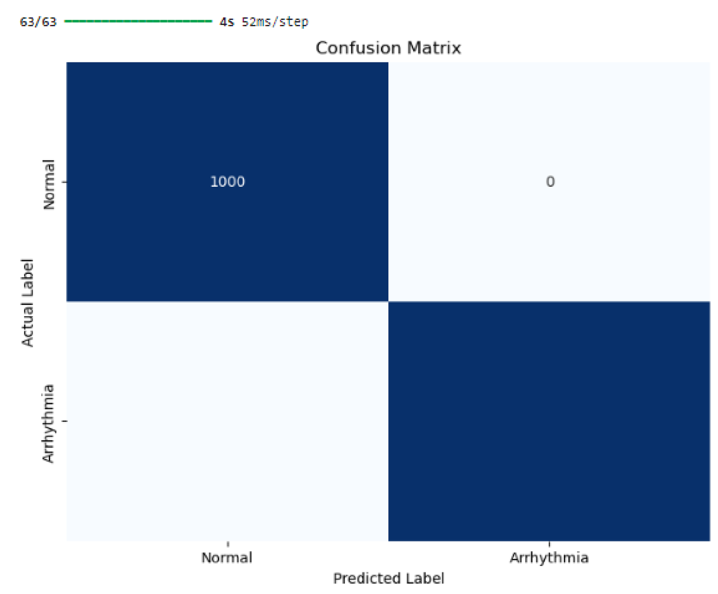


Results

Time series



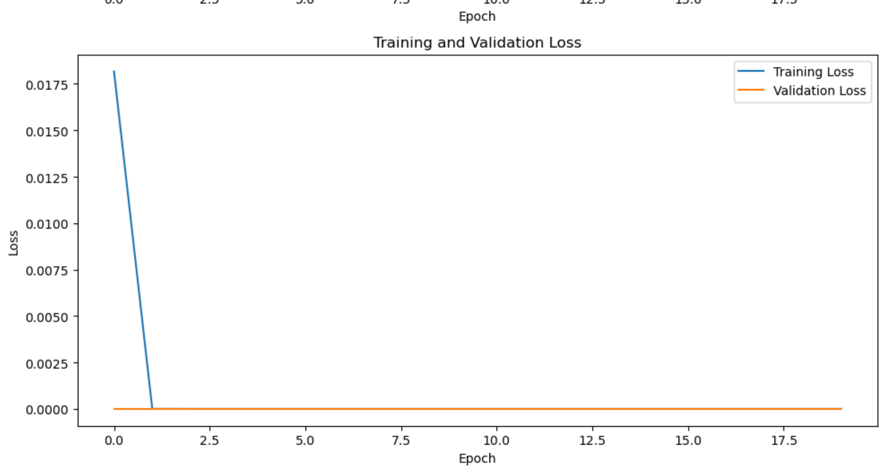


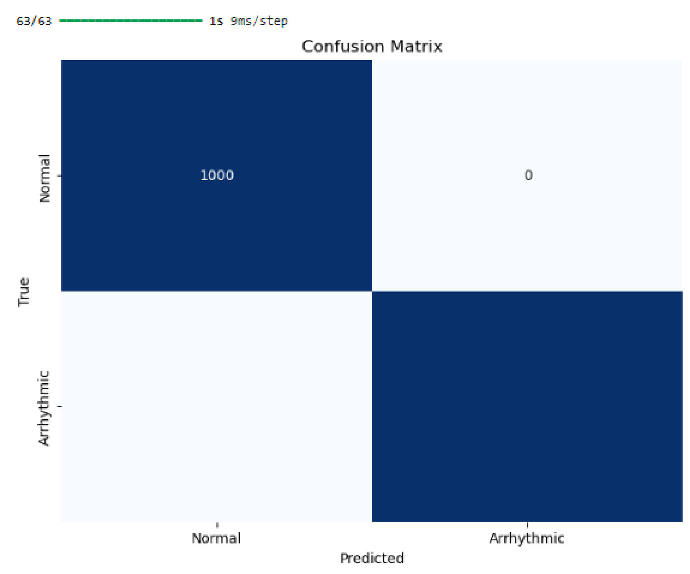


	precision	recall	f1-score	support
Normal	1.00	1.00	1.00	1000
Arrhythmia	1.00	1.00	1.00	1000
accuracy			1.00	2000
macro avg	1.00	1.00	1.00	2000
weighted avg	1.00	1.00	1.00	2000

Time Series: While it eventually achieved 100% accuracy, the training process involved fluctuations (as shown in the top graph), indicating that the model took longer to stabilize. The ups and downs suggest that the model struggled to find patterns quickly in the raw time series data.

Spectrogram





Classification Report:

	precision	recall	f1-score	support
Normal	1.00	1.00	1.00	1000
Arrhythmic	1.00	1.00	1.00	1000
accuracy			1.00	2000
macro avg	1.00	1.00	1.00	2000
weighted avg	1.00	1.00	1.00	2000

Spectrogram: The bottom graph shows a much smoother and quicker convergence to 100% accuracy. This suggests that converting ECG signals into spectrograms significantly improved the model's ability to recognize patterns more efficiently, leading to faster and more consistent training.

Conclusion

The integration of time series and arrhythmic ECG data worked well for both methods, but spectrogram conversion proved to be more effective in quickly reaching high accuracy without the instability seen in the time series representation. This supports the hypothesis that spectrograms enhance CNN performance for ECG classification, especially for arrhythmic detection.

Future work:

For future work, the model could be extended by testing on more diverse and noisy datasets to assess its robustness and generalization. Real-time ECG monitoring systems could be developed for continuous cardiac care, and multi-class classification could be explored to detect a wider range of arrhythmias. A hybrid approach combining time series and spectrogram data might further enhance accuracy. Transfer learning with pretrained models could reduce computational costs, while explainability methods would provide insights into the model's decision-making process.

Reference

[1] Alzubaidi, L., Zhang, J., Humaidi, A. J., Duan, Y., Santamaría, J., Fadhel, M. A., & Farhan, L. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. Journal of Big Data, 8(1), 1-74. https://doi.org/10.1186/s40537-021-00444-8

[2] Semenoglou, A., Spiliotis, E., & Assimakopoulos, V. (2023b). Image-based time series forecasting: A deep convolutional neural network approach. *Neural Networks*, *157*, 39–53. https://doi.org/10.1016/j.neunet.2022.10.006

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