Comparative analysis of deep learning architectures in classification of ECG signals

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Abstract

Electrocardiography (ECG) is the most used diagnostic method for diagnosing cardiovascular diseases, mainly attributed to its less-invasive ability to assess the cardiac condition of the patient. Electrocardiogram is a simple test that checks the rhythm and electrical activity of the heart. Electrodes are placed on the skin and a graph of voltage versus time of the electrical activity of the heart is recorded. This is called the electrogram of the heart. We have acquired an open-source dataset that contains 21,837 instances of ECG readings from the PTB_XL repository. In this research project, we aim to develop a deep learning model that helps in diagnosing cardiovascular diseases using ECG Signals. The ECG signal reports are taken as the input to the model, a classification task is performed on the dataset and the corresponding label i.e., the disease is predicted.

Introduction

After some preliminary literature survey, we found that most of the explorations involving deep learning models used convolutional neural network-based architectures. Zhang et. Al. [1] made a custom architecture and were able to achieve an overall accuracy of 98.27%. The dataset used was from the ECG management system of the First Affiliated Hospital of Nanjing Medical University; however, it is not publicly available. Śmigiel et. Al [2] on the other hand used the publicly available PTB-XL dataset to acquire an overall accuracy of 89.2% using entropy features. The significant performance difference between the two could be attributed to the size of the data used, as the latter had only 21,837 instances while the former had 277,807 records over multiple years. In our exploration, we hope to improve the second model using skip connections and various regularisation parameters. In the meantime, we also hope to acquire the dataset used by Zhang et. Al and explore the same using various deep learning architectures as well.

The motivation behind doing the current project is to ease out the task of identification of heart diseases which can be helpful in future to diagnose the issue and therefore take effective measures accordingly.

Materials required

Hardware requirements:

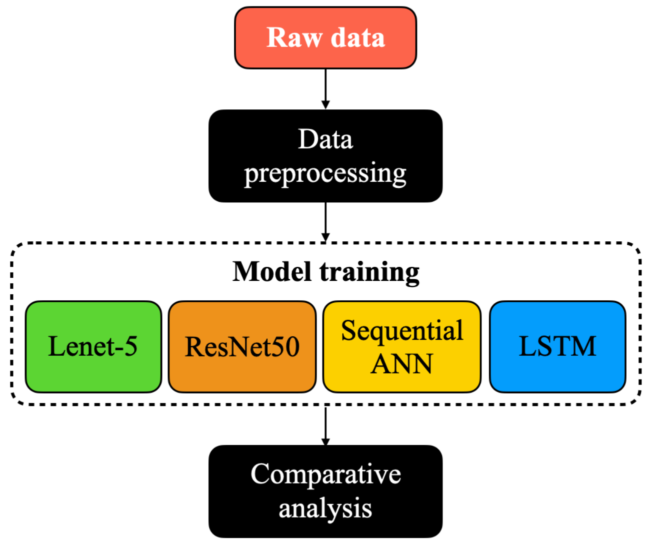
- A working computer with a fast enough processor of any architecture and a GPU

Software requirements:

- Capable of interpreting Python 3+ and some libraries
- Cloud repository for collaboration (GitHub)

Methodologies

Once the dataset was acquired from the repository, we processed it using the utility packages. Then, with the same subsets, we trained each of the models namely Sequential ANN, ResNet-50, LSTM and Lenet-5. Finally, the performance metrics such as loss, accuracy, precision and recall are collected and presented in the Results and Discussions section below. The same is depicted as a flowchart here. Scan the QR code (top-right) to view more information about our project.



Results

The highest performing model in terms of Accuracy value is “” (Figure 2). The best model in terms of AUC score is ResNet-50 (Figure 3)

Architecture	Accuracy	Precision	AUC	ETA per epoch
Sequential	0.953	0.573	0.593	52s
LeNet	0.953	0.606	0.668	89s
LSTM	0.96	0.668	0.570	298s
ResNet50	0.96	0.657	0.735	190s

The LSTM took the longest to train, while the Sequential took a fraction of the time. However, in terms of accuracy, LSTM was the highest with a value of 0.96 while in ResNet50 scored slightly higher than others in terms of AUC.

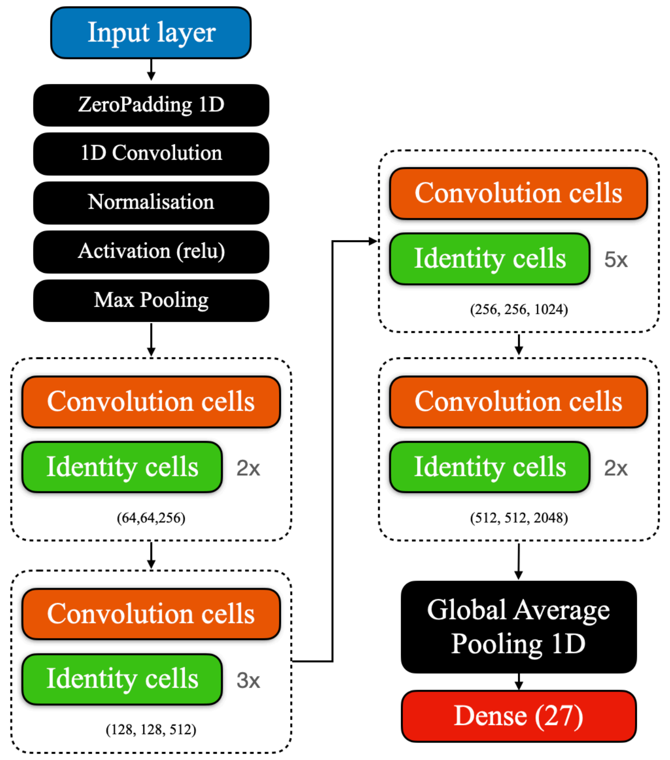


Figure 3: ResNet-50

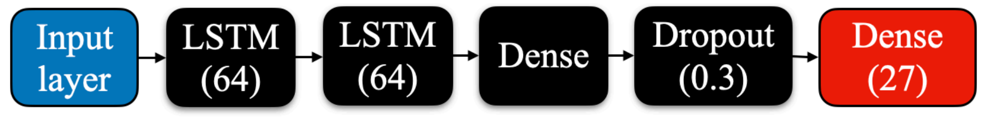


Figure 2: LSTM

Conclusion

In this study, we explored the implication of time component in the classification of ECG signals and performed comparative analysis between classical architectures (Lenet-5 and ResNet-50) and LSTM. As described in the Methodologies section, we trained the respective models and observed the performance measures such as Recall, AUC, Accuracy and loss. The findings are presented in the results and discussions section. Although there is only a marginal improvement in using LSTM from ResNet-50, the computational time and resources was significantly more. This begs a question of the relevancy of a time component. But what we conclude in our study is, the addition of time component adds a new dimension to the way the model learns. The model is therefore more comprehensive compared to the classical architectures. The significant increase in computation time for a diminutive increase in performance measure in terms of accuracy is therefore justified in using LSTM.

Recommendations

The class distribution of the original dataset is highly skewed. If sampled from this skewed distribution the models will by default have a bias. This data imbalance could be dealt with better. Some possible ways could be SMOTE Oversampling on the minor classes and slightly undersampling the majority class. However, we could train autoencoders and use the latent space to cluster the data points. Then we pick even samples around the centers of the latent space clusters.
Aside from data imbalance issues, we could look into compunded architectures of CNNs and LSTMs to model the spatial and temporal dependencies in the signals.

Acknowledgements

[1] M. Liu and Y. Kim, "Classification of Heart Diseases Based On ECG Signals Using Long Short-Term Memory," 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2018

[2] Qiyang Xie, Xingrui Wang, Hongyu Sun, Yongtao Zhang, Xiang Lu, "ECG Signal Detection and Classification of Heart Rhythm Diseases Based on ResNet and LSTM", Advances in Mathematical Physics, vol. 2021

GitHub Repository: https://github.com/Makesh-Srinivasan/ECG_Nagasaki