AI Assisted Prediction and Analysis of Electrocardiograms

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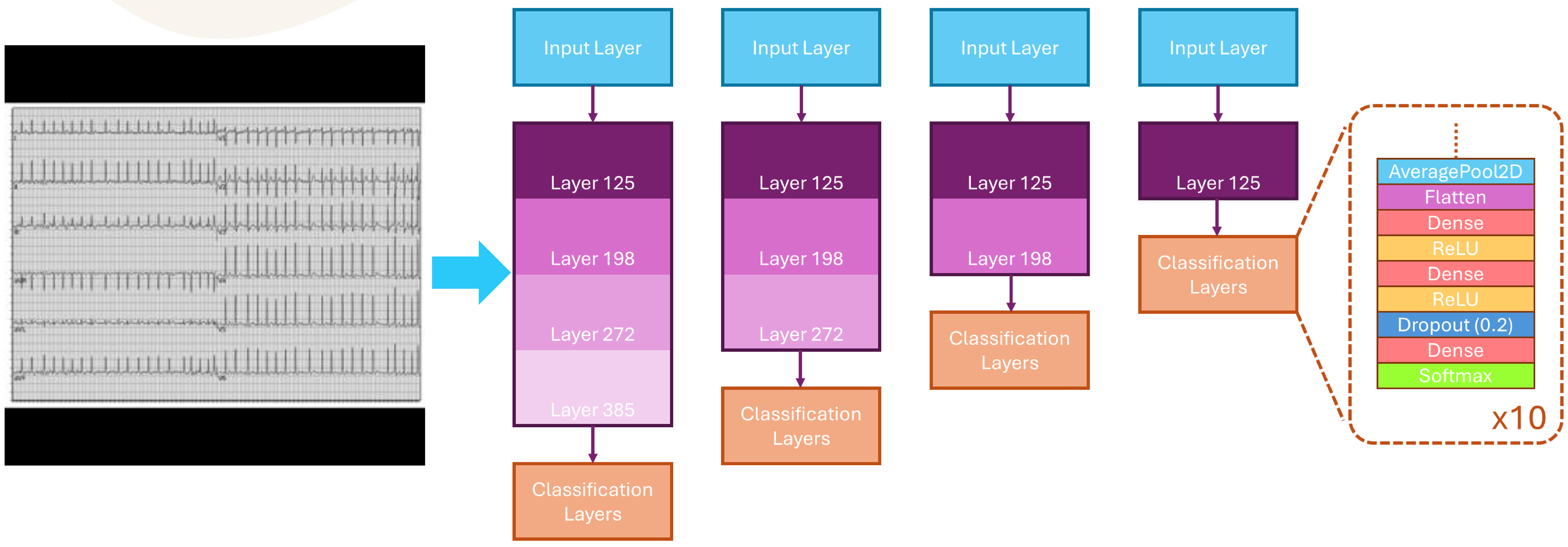
Introduction

The 12-Lead ECG provides a rich amount of diagnostic information to describe a patient's heart condition. However, they are not easily interpretable by individuals outside the field of cardiology, which can be problematic in hospitals or areas where specialists are not immediately present. With the development and growing capabilities of deep learning techniques, numerous trained models have been proposed to streamline digital ECG analysis to facilitate diagnosis and treatment of heart disease. Much of both historic and recent ECG data collected, however, exists in a physical or scanned format. We have implemented an ensemble architecture to perform image-based ECG analysis and prediction, which we benchmark against a previously validated 1D signal-based approach.



Base Network Architecture:
EfficientnetB3, contains squeeze excitation modules at which feature maps are weighted

Feature Extractors:
4 variations of the original network, each truncated at one of the squeeze excitation modules

Classifiers:
Each feature extractor feeds 10 uniquely randomised classifiers

Soft Voting Prediction:
All 40 scores output from the entire ensemble are used to predict and quantify uncertainty

Methods

We selected EfficientNetB3 (ENB3) as the base pre-trained model for our ensemble. We retrained the base ENB3 to perform the classification task of predicting atrial fibrillation (AF) in ECG images. This test case allows us to take advantage of publicly available online databases with high proportions of AF labels compared to other labels, as well as perform benchmarking on a previously validated signal-based model[1].

ECG images were generated from the online repositories PTB-XL[2] and the 2018 Chinese Physiological Signals Challenge[3] containing 12 lead digital signals. To conform to the 300x300 input size of ENB3, the digital signals were plotted to an image using the ecg_plot library (dy1901, 2022, https://github.com/dy1901/ecg_plot), then scaled down and padded to fill the image.

After retraining the base model, we created a network ensemble by truncating the model at the last layers of different squeeze-excitation blocks. New classifiers were reattached to the truncated models and each were retrained. During inference, all classifiers contribute to the final prediction of the sample through soft voting.

Training and Results

Classification Task:
Binary AFIB Label

Parameters:
$1x10^{-5}$ learning rate
Adam optimiser
Batch size of 32 samples
Training Patience of 10 Epochs

Training and validation (80/20 split):
PTB-XL[2] from physionet.org

Testing:
2018 CPSC [3]

Environment:
Python
Keras (Tensorflow Backend)
NVIDIA RTX A6000 48GB GPU

	Single EfficientNet B3	Snapshot Learning	40Classifier Ensemble	Digital
Atrial fibrillation	1094	1094	1094	1094
Not atrial fibrillation	5772	5772	5772	5772
TP	811	862	972	997
FP	388	286	381	310
TN	5384	5486	5391	5462
FN	283	232	122	97
Accuracy	0.90	0.92	0.93	0.94
Precision	0.67	0.75	0.72	0.76
Recall	0.74	0.79	0.89	0.91
F1-score	0.70	0.77	0.79	0.83

Performance of trained models on the unseen CPSC 2018 Dataset

Conclusions

By implementing ensemble techniques, we have improved the performance of an image-based architecture in classifying AF in 12 lead ECGs. In particular, the recall benefitted the most from the increased number and variation of models involved in decision making. Comparing our results to a validated digital signal-based model we find our ensemble is close in performance.

Future

We are currently working on leveraging our model ensemble to tackle common problems in machine learning, including domain adaptation and uncertainty analysis. Our growing collaboration with hospitals and clinics will provide opportunities to undertake novel retrospective studies using historic ECG image data and the predictive power of our ensemble.

References

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