A Validation Study of Automated Atrial Fibrillation Detection using Alerte Digital Health's Artificial Intelligence System

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PURPOSE

- Many strategies and devices can assess cardiac rhythms.
- There is no ideal tool with continuous ECG recording, real time analysis and cardiologist level accuracy on the market.
- Alerte Digital Health's Mobile Health Platform involves a non-invasive wearable ECG acquisition device, continuous wireless data streaming to a mobile device, and real-time interpretation of the data using artificial intelligence (AI).
- The purpose of this study was to develop an initial AI algorithm to detect two common cardiac rhythms (Sinus Rhythm and Atrial Fibrillation) to be deployed in our platform, allowing real-time rhythm detection with the same accuracy as a cardiologist. This is depicted in Figure 1.
- A system of this kind may lead to earlier disease detection with a simpler and more accurate diagnostic pathway.

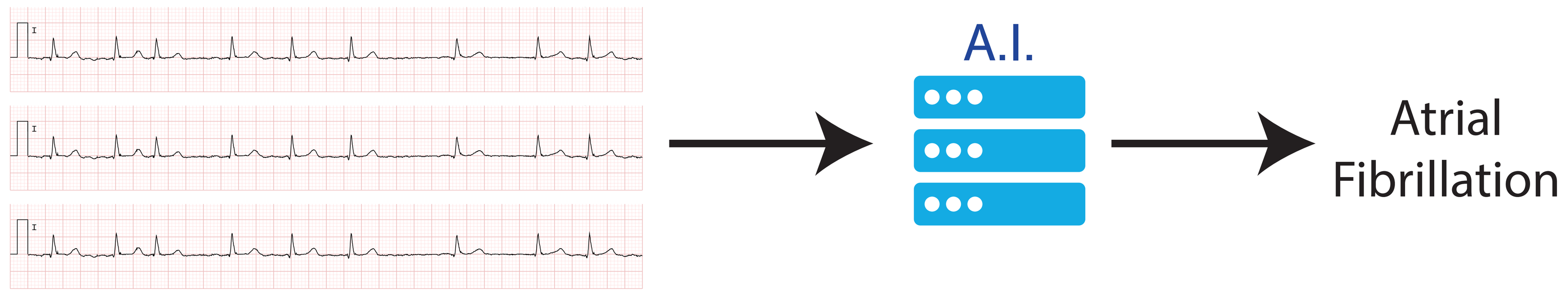

Figure 1: Aim of study

METHODS

This study focused on two rhythms: Atrial Fibrillation (AF) and Normal Sinus Rhythm (NSR). Annotated examples of AF and NSR were sourced from the MIT Atrial Fibrillation [1] and MIT Normal Sinus Rhythm [2] databases, respectively, as in Figure 2. These databases consist of Holter recordings lasting greater than 10 hours. Ground truth labels were taken as the cardiologist's over-read of the holter monitor ECG strips, annotated as AF (labelled as 0) and NSR (labelled as 1). Only the Lead I signal was used.

To become a useful tool, we needed our AI to behave and achieve the same classification results as a Cardiologist. The input to the AI was therefore a 10 second strip of ECG sampled at 250 Hz. The input data was not pre-processed, apart from being re-sampled to 250 Hz.

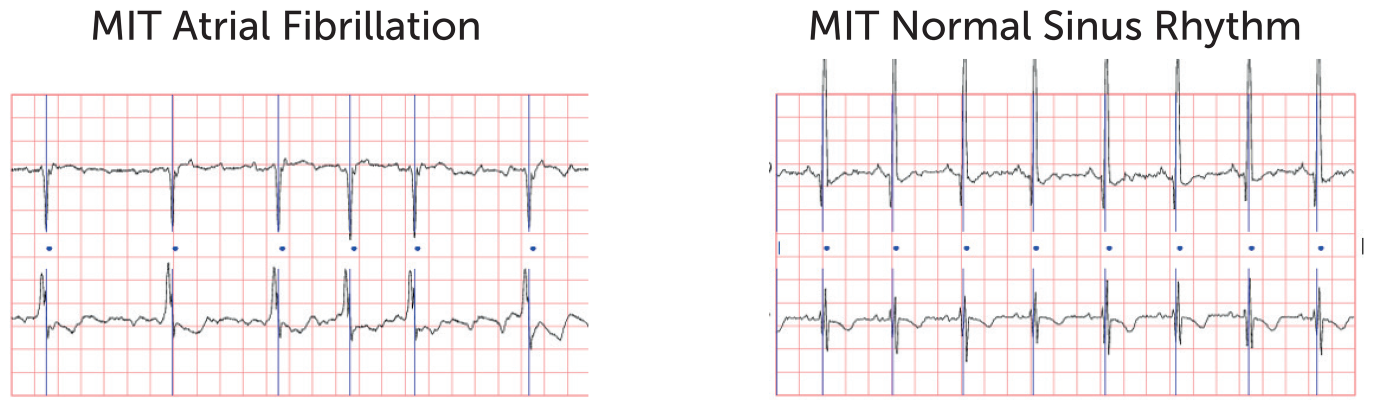

Figure 2: Examples of data sources

We therefore needed to use an AI that could automatically generate the important features of an ECG that a Cardiologist fundamentally understands; a Convolution Neural Network (Conv-Net) was an obvious choice as it can generate the important features internally, inspired by how the eye detects patterns and shapes from light [3].

Our Conv-Net worked by passing the input ECG strip through several convolutional layers, 4 in our case, which sub-sample the data and generate 32 features at each layer. The data is eventually sub-sampled down to 10 points, whereby it is feed through two fully-connected layers with 2048 neurons each. The fully connected layers perform the actual classification operation by using the features generated by the convolutional layers to classify the input into the output classes; AF and NSR. The model is depicted in Figure 3.

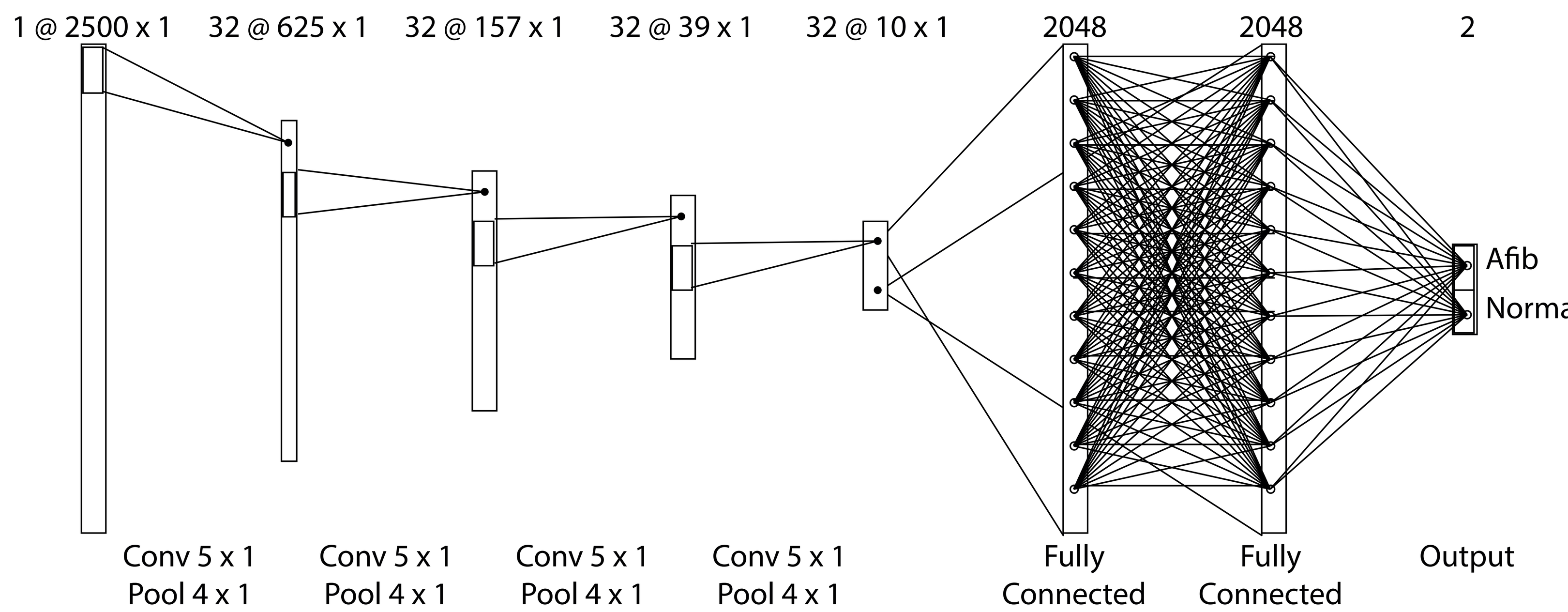

Figure 3: Structure of A.I. Model

A total of 30,000 examples, 15,000 AF and 15,000 NSR, were used in the training and validation of the AI. The data was split using a 70/30 cross validation method; 70% of the data was used as training example and 30% of the data was used as testing example. The testing data would provide the data for quantifying the accuracy of the model. With a batch size of 128 examples, the model was repeatedly trained until absolute train and test accuracies were at least 99%. The "Adam" optimizer was chosen as the training algorithm over the standard Gradient Descent algorithm for faster convergence [4]. The training routine is shown in Figure 4. We used the Receiver Operating Characteristic (ROC) curve, Precision-Recall (P-R) curve and train and test accuracies to assess the model's performance.

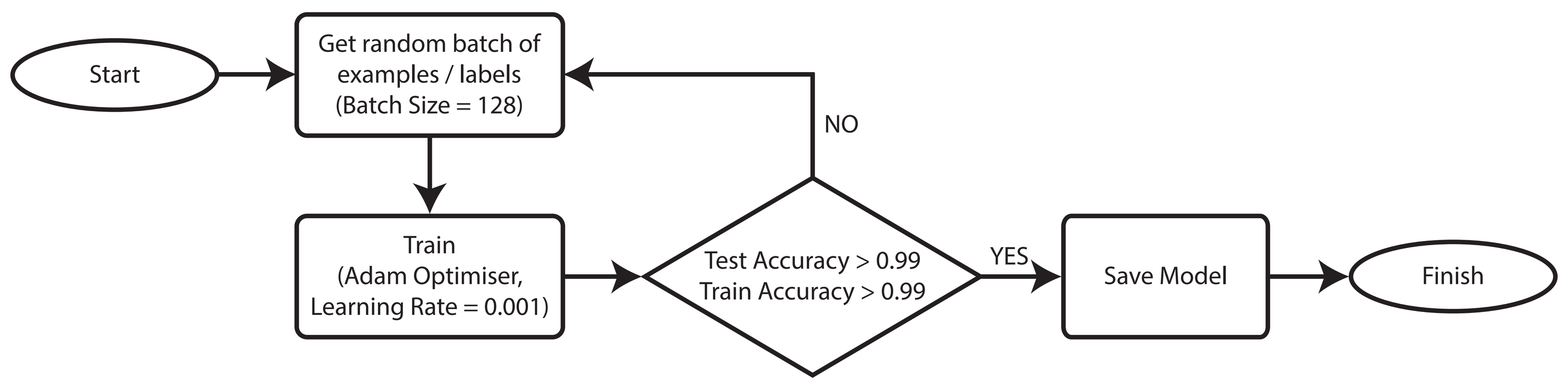

Figure 4: Flowchart of training routine

RESULTS

The model reached 99% in train and test accuracies after 500 training iterations. The progress of the training is shown in Figure 5. The ROC curve area was 0.98 and the P-R curve area was 0.97, as shown in Figures 6 and 7, respectively. The Adam optimizer allowed the model to generate the hyperparameters internally, enabling a larger effective step size and faster convergence. This was at the cost of requiring more computational power and producing a larger model than its standard counterpart Gradient Descent.

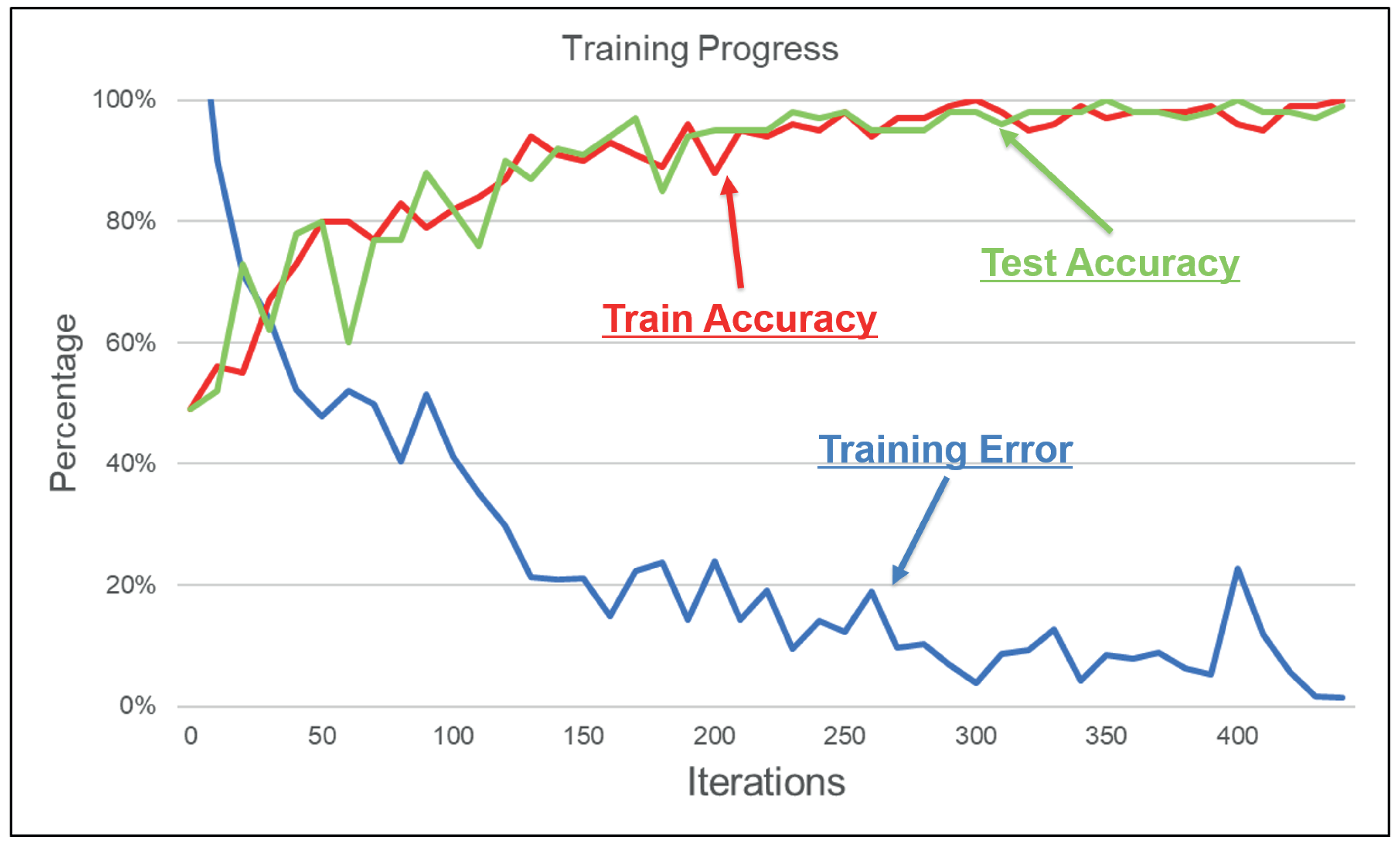

Figure 5: Training Progress

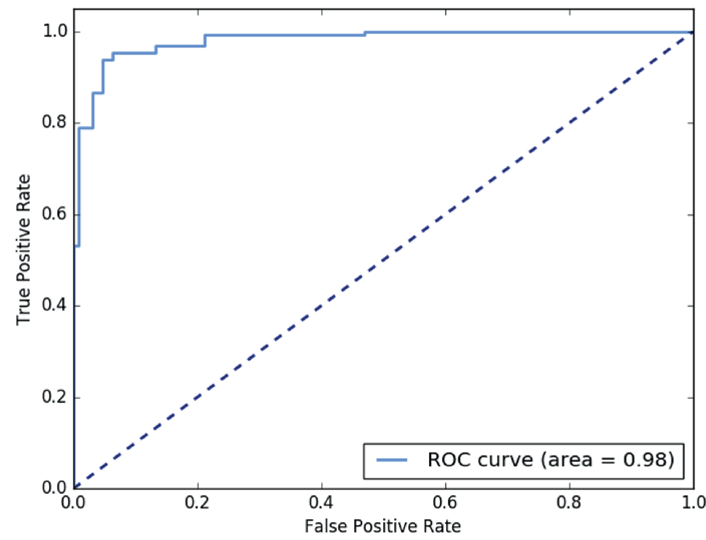

Figure 6: ROC curve

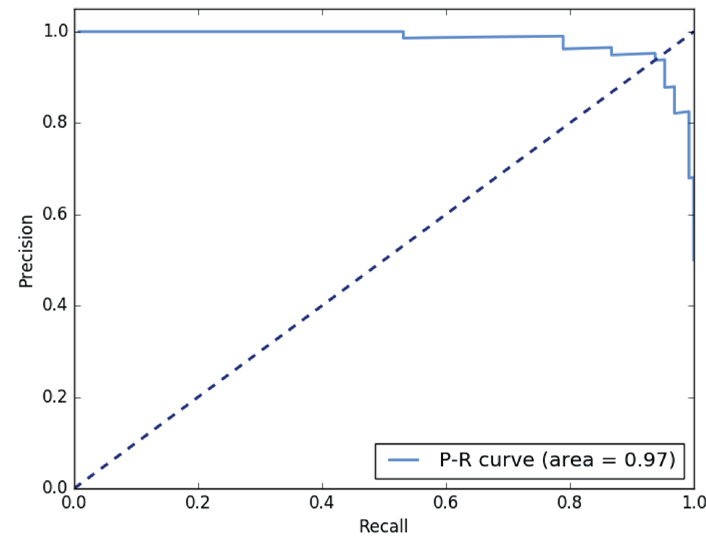

Figure 7: P-R Curve

CONCLUSIONS

Using a trained artificial intelligence model, we have been able to correctly classify between Atrial Fibrillation and Normal Sinus Rhythm, with the same accuracy as a Cardiologist. Once embedded into our framework, the Alerte AI provides a mechanism for automated AF detection from any continuous ECG monitoring device. In addition, this framework allows for ongoing AI feedback and training, continuing the evolution of improved diagnostic capacity for other cardiac arrhythmias.

References:

[1] "The MIT-BIH Atrial Fibrillation Database," [Online]. Available: https://www.physionet.org/physiobank/database/afdb/.

[2] "The MIT-BIH Normal Sinus Rhythm Database," [Online]. Available: https://www.physionet.org/physiobank/database/nsrdb/.

[3] M. D. a. R. F. Zeiler, "Visualizing and understanding convolutional networks," in European conference on computer vision, Zurich, 2014.

[4] J. B. Diederik P. Kingma, "Adam: A Method for Stochastic Optimization," in International Conference for Learning Representations, San Diego, 2015.

Declaration of Interest: Dr. Playford receives consulting fees from Alerte Digital Health and has shares in the company. The other authors have shares in the company.