**Model Development**

Each ECG was converted to a matrix with 12 columns and 5,000 rows, each column representing one of the 12 leads (spatial dimension) and each row representing the lead amplitude in microvolts for that timestamp in each lead (temporal axis, ECGs was sampled at 500Hz). As the ECGs were all high quality, no pre-processing was required. We tested both a Res-Net architecture(1, 2) and vanilla CNN(3, 4). As both had similar results on internal validation, we selected a simple CNN. The CNN’s architecture followed a previously published model used to predict low ejection fraction from ECG(3), having 9 convolutional blocks and two fully connected blocks. It was trained from random initial values using the Adam optimizer.(5) We tested multiple learning rates (ranging from 〖1×10〗^(-3) to 〖1 ×10〗^(-4)) and multiple batch sizes (16-64 samples) on the internal validation set and the ones that had the optimal area under the curve (AUC) (batch size of 32 and learning rate of 〖3 ×10〗^(-4)) were used for testing the model on the holdout test set.

**References**

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