Supplemental Material

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Overview of CNN Model for detection of patients with an LVEF of ≤35% using the ECG signal

As previously described,[1, 2] a convolutional neural network (CNN) trained with Keras with a Tensorflow (Google, Mountain View, CA) backend was developed and validated. The only model input reported was a 12-lead ECG. Each 12-lead ECG was a matrix with 12 x 5000 matrix (i.e., 12 leads by 10 seconds duration sampled at 500 Hz) divided to 2 seconds segments with an overlap of one second.[3] The network was composed of 6 single lead convolutional layers, each of which was followed by a non-linear "Relu" activation function, a batch-normalization layer[4] and a max pooling layer[5]. The features extracted from each raw, digital signal ECG lead were fused in another convolutional layer that had access to all leads simultaneously. Following the last convolutional layer, the data were fed to a fully connected network with two hidden layers with dropout layers to avoid overfitting and an output layer that was activated using the "Softmax" function.[6] The outputs of the softmax layer were compared with the actual label (EF <= 35%, or EF>35%) and by using an "Adam" optimizer, the different layers were trained to classify each ECG to one of the EF groups. During training, the network was given the actual EF label, whereas during the testing and validation stages, the network was blinded from the EF value, and the model output was compared to the actual EF class (EF ≤ 35% , or EF>35%) after the model was run for each ECG sample. While the outcome used to train the model is binary (EF ≤ 35% or EF >35%), the network output is a continuous number between zero and one that represent the probability of the binary outcome (EF $\leq$ 35%). As the output is continuous, the final decision is made by selecting a threshold and testing if the output is above or below that threshold. All possible thresholds with the attendant sensitivity and specificity are displayed in the receiver-operating curve.

References:

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