# Deep Neural Network Trained on Surface ECG Improves Diagnostic Accuracy of Prior Myocardial Infarction Over Q Wave Analysis

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## Abstract

*Clinical screening of myocardial infarction is important for preventative treatment and risk stratification in cardiology practice, however current detection by electrocardiogram Q-wave analysis provides only modest accuracy for assessing prior cardiac events. We set out to evaluate the ability of a deep neural network trained on the electrocardiogram to identify patients with clinical history of myocardial infarction.*

*We assessed 608 patients at two academic centers with adjudicated history of myocardial infarction. Surface electrocardiograms were used to train a neural network-based model that classifies patients with and without a history of infarction. Endpoints were assessed by clinical record review and accuracy of the model was compared against the manual assessment of pathologic Q waves.*

*The neural network outperformed the accuracy of pathologic Q waves (62%). In training, the model accuracy converged to >98%. Validation was performed by cross-validation (k=5) with validation accuracy 71 ± 5%. Receiver-operator characteristics analysis resulted in a c-statistic of 0.730.*

*Deep learning of a 12-lead ECG can identify features of prior myocardial injury more accurately than clinical Q-wave analysis and may serve as a valuable clinical screening tool.*

## 1. Introduction

Clinical screening of myocardial infarction (MI) is important for preventative treatment and risk stratification for cardiology practice.[1] Many of these events may be silent (without clinical symptoms) but have the same important consequences on health as clinical heart attacks [2]. The current standard of care is to detect MI by evaluation of the surface electrocardiogram (ECG) for the presence of pathologic Q-waves. Although Q-wave analysis by ECG is quick and inexpensive compared with specialized imaging studies, it has poor sensitivity for detecting a history of MI in patients.[3]

Neural networks have been used for predictive analysis for a variety of applications [4] including cardiac electrophysiology.[5] Previously, we have shown the ability of neural networks and machine learning to classify and study atrial rhythm disorders.[6], [7]

In this study, we hypothesized that a deep neural network (DNN) trained on the surface ECG may identify patients with and without clinical history of MI with improved accuracy than standard-of-care ECG analysis.

### 1.1. Objective

To evaluate the ability of a DNN trained on the surface ECG to classify patients with clinical history of MI.

## 2. Methods

We assessed 608 well-characterized patients at 2 academic centres (Stanford University and Oregon Health Sciences University). Inclusion criteria included patients undergoing implantation of a primary prevention implantable cardioverter-defibrillator. Clinical review was performed of each patient's medical chart prior to the implant of the cardiac implantable electronic device. A 12-lead ECG, recorded prior to the implant of the cardiac device, was collected, processed, and labelled by a physician and used as input for model training and validation.

### 2.1. Clinical Review

Chart review of each patient was performed to evaluate

baseline demographics, medical comorbidities (Table 1), and history of MI (based on imaging studies, patient history, and physician diagnosis). History of MI adjudicated by all modalities available in the medical chart was used as the gold standard labels for model training and performance assessment.

## 2.2. Signal preprocessing

Each standard configuration 12-lead ECG was originally collected for 10 seconds at 500Hz sampling frequency. From each ECG, median beats were calculated in 3 orthogonal planes (X, Y, Z) by applying the Kors transform [8]. Figure 1 shows an example 3-lead median beat used for model development and testing.

Pathologic Q-wave analysis was performed on transformed ECG signals by physician review. Pathologic Q waves were defined as a deflection >25% of the subsequent R wave, >40ms in width, and >0.2mV amplitude in 1 of 3 ECG planes.

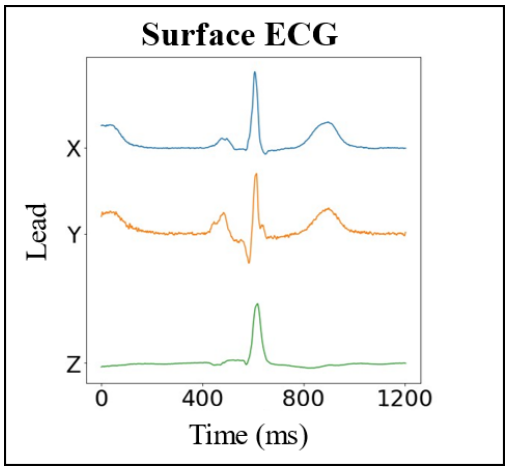


Figure 1. Representative input 3-lead ECG for patient with history of myocardial infarction and Q wave present in the Y Lead (orange tracing).

## 2.3. Neural network architecture

Figure 2 illustrates the model architecture used in this work. Our DNN model is a convolutional neural network (CNN) that takes median X, Y, Z signals (dimension=3 channel x 600 time-samples) as the input and a SoftMax layer at the end provides either of positive (MI present) or negative (MI absent) labels as the output. The first convolution layer is a 64-filter followed by 128 and 256-filter layers and then gradually reducing back to 64. The output from this final convolution layer is then flattened and connected to dense layers with ReLu and SoftMax activations respectively. We used a standard ReLu activation for all convolution filters. A dropout of 0.2 was applied to prevent overfitting. Binary cross-entropy loss function along with adam optimizer was used for back-propagation. The learning rate was set to 0.0001 and the decay was set to 1e-4 and early stopping was not used.

We divided our N=608 patients x 3 channels ECG signals into training and testing sets by stratified K fold splitting (N=5). The input batch size was set to 64 and the training was performed on a high-performance computer with a NVIDIA GeForce RTX 2080 Ti processor, 1545 MHz GPU and 11GB RAM. With this configuration, model convergence was achieved in 120 epochs after 4.5 hours of training.

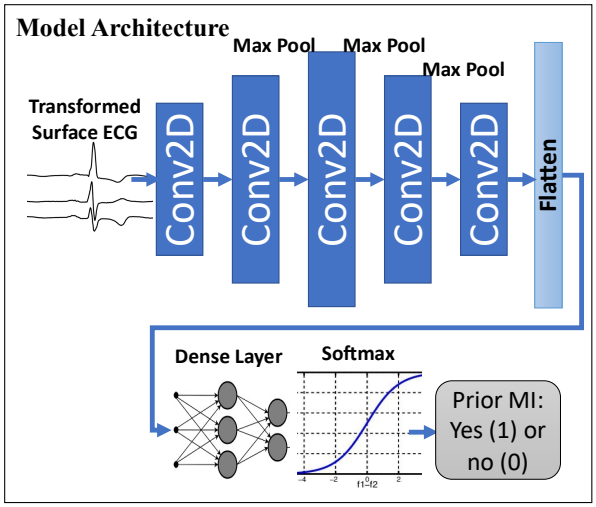


Figure 2. Deep neural network architecture.

## 2.4. K-fold Cross Validation

Validation of the model was performed using k=5 fold cross validation.[9] Average accuracy in cross validation was compared with the clinical Q wave analysis for overall performance.

# 3. Results

## 3.1. Demographics

All patients underwent 12-lead ECG recording and had thorough chart review to determine history of MI. Patients were 61.4±14.5 years old and were 31.2% female. See Table 1 for patient clinical characteristics.

Table 1. Patient clinical characteristics

| Characteristic | Mean | Std |
|---|---|---|
| Age | 61.4 | 14.5 |
| Female | 31.2% | |
| Myocardial infarction | 28.7% | |

| | | |
|---|---|---|
| Hypertension | 56.1% | |
| Diabetes | 26.0% | |
| Atrial fibrillation | 32.9% | |
| Creatinine | 1.36 | 1.17 |
| NYHA Class* | 2.44 | 0.70 |

*NYHA: New York Heart Association functional classification

## 3.2. Model Performance

In training, DNN converged to >98% accuracy (blue curve in figure 3), and in testing, its accuracy was 71±5% across k=5 cross validation (yellow curve in figure 3). This outperformed the 62% accuracy of pathologic Q waves in this study (red dotted line, Figure 3).

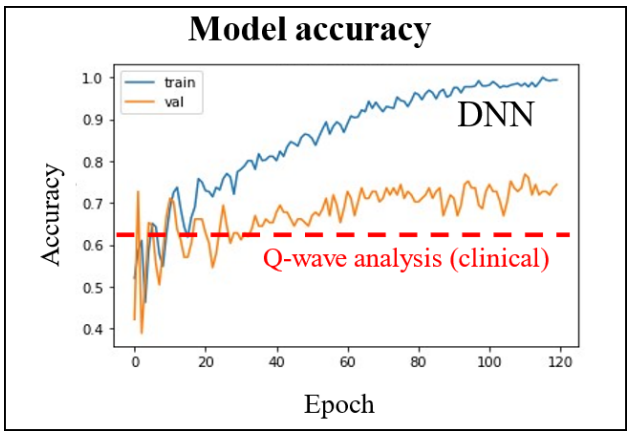


Figure 3. A deep neural network was trained on ECGs over 120 epochs resulting in validation and training accuracy curves (orange, blue). This is shown relative to manual ECG Q-wave classification accuracy (red dotted line).

In the validation cohort, DNN provided an area under the receiver operating characteristics curve of 0.730 (Figure 4).

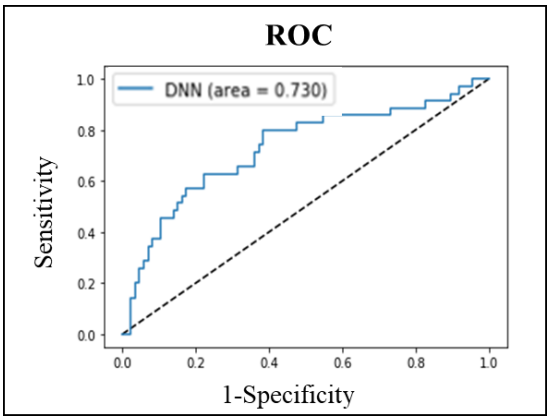


Figure 4. Continuous probabilities predicted by the neural network are used to construct an ROC curve for detecting history of MI. Examples of model classification results is shown in figure 5. In a 90 YO female who had MI (figure 5A), the model classified the ECG correctly as MI being present, however the ECG leads do not show a clinical Q-wave. This representative example demonstrates the model's superior performance to clinical visual analysis. On the other hand, figure 5B shows an example where the model misclassified an ECG for which the clinical analysis was also unsuccessful.

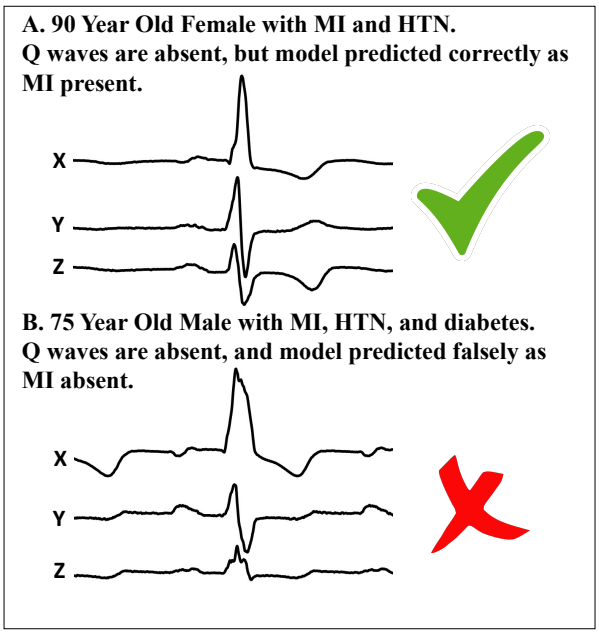


Figure 5. Examples of ECGs showing correct and incorrect detections by the model.

## 4. Discussion

In is study, we developed a DNN that was trained on surface ECG to identify patients with and without a clinical history of MI. We compared the model's overall performance to the standard of care Q-wave analysis and found it to be superior. Such a clinical screening method could be used to identify patients with history of silent (asymptomatic) heart injury, which may have clinical implications such as further imaging, stress testing, medication changes, or intervention.

Other possible identification methods, such as echocardiogram, myocardial perfusion imaging, coronary angiography, and cardiac magnetic resonance imaging have much greater complexity and cost, compared with ECG analysis. Therefore, the feasibility of using these for screening is lower. Furthermore, ECGs could be monitored repeatedly or even in real time, to monitor for repeat events, which are common in coronary disease.[10]

This study was limited by the size of the validation cohort, however the model achieved strong test characteristics compared with the clinical standard of care. The dataset was large for its kind given the well-characterized clinical dataset.

Further work may expand on the current study by validating the model in an independent institution to ensure generalizability. Furthermore, evaluation of patient outcomes when being screened by ECG/DNN methods could be prospectively assessed to ensure that screening in this way would both change clinical management and improve outcomes or decrease cost.

Physiological implications of the current work may be explored by utilizing model analysis to interpret the features most valuable in classifying individual patients. Deeper understanding of the electrocardiogram and its relationship to the ECG extending beyond the Q wave analysis would provide a more practical, interpretable, and thus, increased confidence in its output.

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