ECG-based deep learning for detecting epicardial coronary occlusion in acute myocardial infarction

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Background: One third of Non-ST-elevation myocardial infarction (NSTEMI) patients have occlusion myocardial infarction (OMI) associated with poor short- and long-term outcomes due to delayed invasive management.

Purpose: We sought to develop and externally validate a versatile artificial intelligence (AI)-model detecting OMI on single standard 12-lead electrocardiograms (ECGs) and compare its performance to existing state-of-the-art criteria.

Methods: An AI model was developed using 18,616 ECGs from 10,692 unique contacts (22.9% OMI) of 10,543 patients (age 66 ± 14 years, 65.9% males) with acute coronary syndrome (ACS) originating from an international database and a tertiary care center. This AI model was tested on a holdout set of 3,254 ECGs from 2,263 unique contacts (20% OMI) of 2,222 patients (age 62 ± 14 years, 67% males) and compared with STEMI criteria and annotations of ECG experts in detecting OMI on 12-lead ECGs using sensitivity, specificity, and predictive values.

Results: The OMI AI model achieved an AUROC of 0.941 (95% CI: 0.926, 0.954) in identifying the primary outcome of OMI on 12-lead ECGs in the holdout set [Figure 1A], yielding robust performance across genders and age subgroups (ranging from 0.907 to 0.951 AUROC) [Figure 1B]. Sensitivity in detecting OMI was significantly higher for OMI AI model compared to STEMI criteria (82.6% [95% CI: 78.9%, 86.1%] vs. 34.4% [95% CI: 30.0%, 38.8%]) and statistically equal compared to ECG experts 75.9% [95% CI: 71.9%, 80%] in identifying OMI [Table 1]. The OMI AI Model showed statistically superior performance compared to STEMI criteria and equal (non-inferior) performance to ECG experts when evaluated using industry-standard metrics.

Conclusions: This sizeable validation of an AI ECG model demonstrates the ability of AI to detect acute OMI and suggests a potential in improving ACS patient triage and need for immediate revascularization.

A. ROC Curves on Testing Dataset (n = 2,263 contacts [20.02% OMI]; n = 3,254 ECGs)

B. Parameter | Cat | No. ECGs (%) | Sens. | Spec. | PPV | NPV | AUC
--- | --- | --- | --- | --- | --- | --- | ---
Gender | Male | 2219 (68.19%) | 0.758 | 0.919 | 0.818 | 0.888 | 0.910
 | Female | 1035 (31.81%) | 0.793 | 0.931 | 0.730 | 0.950 | 0.934
Age subgroups | ≤65 | 328 (10.08%) | 0.770 | 0.959 | 0.810 | 0.948 | 0.951
 | >65 | 1417 (43.55%) | 0.782 | 0.896 | 0.756 | 0.909 | 0.920
QRS duration | <120 | 2806 (86.23%) | 0.789 | 0.918 | 0.794 | 0.915 | 0.924
 | ≥120 | 448 (13.77%) | 0.595 | 0.958 | 0.825 | 0.878 | 0.873
Rhythm | Sinus | 2897 (89.03%) | 0.767 | 0.918 | 0.790 | 0.908 | 0.915
 | Paced AF | 133 (4.09%) | 0.600 | 0.944 | 0.714 | 0.911 | 0.851
VII | 898 (27.60%) | 0.735 | 0.926 | 0.778 | 0.908 | 0.900
LBBB | 246 (7.56%) | 0.557 | 0.932 | 0.765 | 0.841 | 0.839
RBBB | 548 (16.84%) | 0.726 | 0.976 | 0.907 | 0.916 | 0.916
BPM | <100 | 379 (11.65%) | 0.848 | 0.952 | 0.921 | 0.904 | 0.961
 | ≥100 | 2875 (88.35%) | 0.749 | 0.920 | 0.773 | 0.910 | 0.909

Figure 1. AI model performance on the overall holdout set and subgroup analysis. Panel A shows the ROC curve of OMI AI model and sensitivity and specificity of STEMI criteria (green dot) and ECG experts (purple cross) on the holdout set. The AUC is 0.941 (n = 2,263 contacts [20.02% OMI]), Panel B shows the OMI AI model performance on different patient subgroups.
<table>
<thead>
<tr>
<th>Comparator</th>
<th>Ref -</th>
<th>Ref +</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>PPV</th>
<th>NPV</th>
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<td></td>
<td>1679</td>
<td>79</td>
<td>82.6%</td>
<td>92.8%</td>
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<td>0.955</td>
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<tr>
<td></td>
<td>(78.9-86.1)</td>
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<td>(91.5-93.9)</td>
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<td>OMI AI Model</td>
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<td>STEMI Criteria</td>
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<td>297</td>
<td>34.4%</td>
<td>97.6%</td>
<td>0.780</td>
<td>0.856</td>
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<td></td>
<td>(30.0-38.8)</td>
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<td>(96.8-98.2)</td>
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<td>ECG Experts</td>
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<td>95.0%</td>
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<td>(71.9-80.0)</td>
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<td>(94.0-96.0)</td>
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<td>0.832</td>
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Table 1. Head-to-head benchmark comparison in detecting the primary outcome definition of OMI.

Benchmark Comparison