Supplementary

Table S1 Detailed PubMed and Embase search strategy

Components	Details
PubMed	
Query	(“Electrocardiography”[MeSH Terms] OR electrocardiogra*[tiab] OR ECG[tiab]) AND (“Myocardial Infarction”[MeSH Terms] OR “myocardial infarction”[tiab] OR AMI[tiab] OR STEMI[tiab] OR NSTEMI[tiab] OR OMI[tiab] OR “occlusion myocardial infarction”[tiab] OR “occlusion MI”[tiab] OR “acute coronary syndrome”[tiab] OR ACS[tiab] OR “coronary occlusion”[tiab]) AND (“Artificial Intelligence”[MeSH Terms] OR “Machine Learning”[MeSH Terms] OR “Neural Networks, Computer”[MeSH Terms] OR “artificial intelligence”[tiab] OR “machine learning”[tiab] OR “deep learning”[tiab] OR “neural network*”[tiab]) AND (“2017/01/01”[Date - Publication] : “2025/08/31”[Date - Publication]) AND English[lang] AND humans[MeSH Terms]
Results	225 records (last searched: February 18, 2026)
EMBASE (Embase.com, Elsevier)	
Query	(‘electrocardiography’/exp OR ‘electrocardiogram’/exp OR ecg*) AND (‘acute coronary syndrome’/exp OR ‘coronary occlusion’/exp OR acs OR mi OR ‘myocardial infarction’) AND (‘artificial intelligence’/exp OR ‘machine learning’/exp OR ‘deep learning’/exp OR ‘neural network’/exp OR ai OR ‘machine learning’ OR ‘deep learning’) AND [english]/lim AND [humans]/lim AND [01-01-2017 to 31-08-2025]/pd
Results	1,261 records (last searched: February 18, 2026)

MeSh, Medical Subject Headings.

Table S2 Artificial intelligence models for myocardial infarction detection using electrocardiography

Author	Simple model description	Year	Country/region	Prospective/retrospective	Number of patients	Target	ECG lead configurations/ numbers	Input representation
Kora P (11)	ML model (FFPSO feature optimization + ANN)	2017	India	Retrospective	44 (MI: 26; HC: 18)	MI *vs.* HC	Single lead (II)	Signal (beat-level segments → FFPSO-optimized features)
Liu W *et al.* (14)	CNN-based ECG model with multi-lead feature branches	2018	China	Retrospective	180 (MI: 128; HC: 52)	MI *vs.* HC; localization	12-lead	Signal (beats @ 1000 Hz, per lead)
Sopic D *et al.* (12)	RF-based single-lead wearable ECG model (event-driven hierarchical RF)	2018	Switzerland	Retrospective	104 (MI: 52; HC: 52)	MI *vs.* HC	Single lead (II)	Signal → wavelet transform → features
Liu W *et al.* (65)	CNN-based 4-lead ECG model (sub-2D convolution + lead-asymmetric pooling; ML-CNN)	2018	China	Retrospective	112 (GAMI: 60; HC: 52)	MI (GAMI) *vs.* HC	4-lead (V2, V3, V5, VL)	Signal (multi-lead beat segment @ 250 Hz)
Wu CC *et al.* (48)	ANN-based clinical + ECG-lab model	2019	Taiwan	Retrospective	268 (NSTEMI: 47; UA: 221)	NSTEMI *vs.* UA	12-lead	Features (demographics, vitals, labs, ECG intervals: PR/QRS/QTc)
Wang HM *et al.* (22)	CNN-based ECG model (multi-lead ensemble; MENN)	2019	China	Retrospective	200 (MI: 148; HC: 52)	AMI *vs.* HC; IMI *vs.* HC	AMI: V1-V4 (4 leads); IMI: II, III, aVF (3 leads)	Signal (beat-level, R-peak centered)
Strodthoff N *et al.* (66)	CNN-based 8-lead ECG model (fully convolutional/ResNet; raw-signal, 4-s windows)	2019	Germany	Retrospective	179 (MI: 127; HC: 52)	MI *vs.* HC	8 non-redundant leads (I, II, V1–V6)	Signal (4-s windows)
Wang Z *et al.* (67)	Tree-ensemble model (Random Forest) with multi-feature fusion	2020	China	Retrospective	104 (MI: 52; HC: 52)	MI *vs.* HC	12-lead	Features per lead (PCA + statistical + entropy)
Zhao Y *et al.* (42)	CNN-based ECG model (1D ResNet)	2020	China	Retrospective	8,238 ECGs (STEMI: 667; controls: 7,571)	STEMI *vs.* non-STEMI	12-lead	Signal @ 500 Hz
Han C *et al.* (68)	CNN-based ECG model with multi-lead residual branches + feature fusion (ML-ResNet)	2020	China	Retrospective	165 (MI: 113; HC: 52)	MI *vs.* HC	12-lead	Signal (QRS-centered windows @ 200 Hz, per lead; denoised)
Hao P *et al.* (69)	CNN-based ECG image model (multi-branch 12-lead fusion)	2020	China	Retrospective	957	MI *vs.* non-MI	12-lead	Image (12 cropped lead images)
Zeng W *et al.* (70)	ANN-based model (RBF neural network)	2020	China	Retrospective	200 (MI: 148; HC: 52)	MI *vs.* HC	12-lead + Frank XYZ	Features
Sharma LD *et al.* (71)	ML-based model (SWT features + kNN)	2020	India	Retrospective	200 (MI: 148; HC: 52)	MI *vs.* HC; localization	12-lead	Features from SWT
Kapfo A *et al.* (72)	Feature-based ECG model (VMD multi-scale energy + covariance eigenvalues; SVM-RBF)	2020	India	Retrospective	200 (MI: 148; HC: 52)	MI *vs.* HC	12-lead	Signal → features from variational mode decomposition
Liu W *et al.* (24)	CNN–BLSTM–based ECG model (lead-wise CNN branches + BLSTM; MFB-CBRNN with LRM)	2020	China	Retrospective	200 (MI: 148; HC: 52)	MI *vs.* HC	12-lead	Signal (12-lead beat, ~0.6-s @ 250 Hz)
Al-Zaiti S *et al.* (23)	Fusion-based ECG model (LR+GBM+ANN; temporal–spatial features)	2020	USA	Prospective cohorts, analyzed retrospectively	1,244	ACS *vs.* non-ACS	12-lead	Signal (10-s @ 500 Hz) → temporal–spatial ECG features + demographics (age/sex)
Makimoto H *et al.* (73)	CNN-based ECG image model (6-layer DCNN)	2020	Germany	Retrospective	289	MI *vs.* non-MI	12-lead	Image (PNG ECG crops, 744×368)
Cho Y *et al.* (56)	CNN-based 6-lead ECG model (VAE-assisted precordial reconstruction; 2D-DCNN DLA)	2020	South Korea	Retrospective	8,274 (development: 5,205; internal: 1,301; external: 1,768)	MI (type 1/2; STEMI/NSTEMI) *vs.* non-MI	12-lead/limb 6-lead	Signal (6-lead: VAE reconstructs precordial leads)
Fu L *et al.* (25)	CNN-based ECG model (multi-lead attention 2D-CNN + BiGRU; MLA-CNN-BiGRU)	2020	China	Retrospective	200 (MI: 148; HC: 52)	MI *vs.* HC; localization	12-lead	Signal (per beat @ 1000 Hz)
Martínez-Sellés M *et al.* (74)	CNN-based ECG model with Inception + SE	2021	Spain	Prospective	420 (STE without necrosis: 210; STEMI with occlusion: 210)	STEMI with acute occlusion *vs.* STE without acute necrosis	12-lead	Signal (≥10-s @ ≥250 Hz)
Jahmunah V *et al.* (75)	CNN-based ECG model with Gabor filter	2021	Singapore	Retrospective	262 (HC: 92; CAD: 7; MI: 148; CHF: 15)	Normal *vs.* CAD *vs.* MI *vs.* CHF	Single lead (II)	Signal (2-s @ 1000 Hz)
Martin H *et al.* (19)	RNN-based ECG model (single-beat LSTM)	2021	USA	Retrospective	13,620 (training: MI 3,589, HC 7,115; test: MI 1,076, HC 1,840)	MI *vs.* HC	Single lead (II)	Signal (1-s @ 500 Hz)
Xiong P *et al.* (76)	CNN-based ECG model (DenseNet, multi-lead correlation)	2021	China	Retrospective	200 (MI: 148; HC: 52); 60,908 beats	HC *vs.* 11 MI locations	12-lead	Signal (12×651 matrix per beat; denoised)
He Z *et al.* (15)	CNN-based ECG model with multi-feature-branch lead attention	2021	China	Retrospective	PTB: 165 (MI: 113; HC: 52); PTB-XL: 4,751 (subset)	HC *vs.* AMI/ASMI/ALMI/IMI/ILMI	12-lead	Signal (per lead heartbeat @ 250 Hz; denoised; z-score)
Tadesse GA *et al.* (27)	CNN-based ECG spectrogram model with multi-lead fusion (transfer learning + LSTM)	2021	UK	Retrospective	17,381 (MI: 11,853; normal: 5,528)	Normal *vs.* MI by onset (acute/recent/old)	12-lead	Image (12-lead, 10-s @ 500 Hz) → spectrogram per lead
Fatimah B *et al.* (77)	ML model (FDM → FIBF features + kNN)	2021	India	Retrospective	200 (MI: 148; HC: 52)	MI *vs.* HC	Single lead (II)	Features (FDM/FIBF)
Martin H *et al.* (18)	RNN-based ECG model (LSTM; single-beat Lead II)	2021	USA	Retrospective	200 (MI: 148; HC: 52)	MI *vs.* HC	Single lead (II)	Signal (single-beat; filtered)
Safdarian N *et al.* (78)	ML-based ECG model (SVM-GOA; Q/T/QRS integrals)	2021	Iran	Retrospective	200 (MI: 148; HC: 52)	MI (anterior/inferior/posterior) *vs.* HC	12-lead	ECG features
Mahmoudinejad SA *et al.* (79)	Feature-based ECG model (LR/SVM; integrals + J-point/T-wave)	2021	Iran	Retrospective	200 (MI: 148; HC: 52)	MI *vs.* HC	12-lead	Features (integrals of ECG cycle/QRS/T-wave; J-point elevation; T-wave inversion)
Han C *et al.* (26)	CNN-based asynchronous multi-lead ECG model (lead-wise 1D-ResNet + multi-head self-attention)	2021	South Korea	Retrospective	95,938 (development: 76,829; test: 19,109)	AMI *vs.* non-AMI	Asynchronous lead sets (12-lead; tested on 12-, 4-, 3-, 2-, and single-lead)	Signal (2-s @ 250 Hz)
Liu WC *et al.* (28)	CNN-based ECG model (hospital DLM + rules integrating chest pain and hs-TnI)	2021	Taiwan	Prospective (development); prospective (validation)	25,002 (development); 14,296 (prospective)	AMI detection	12-lead	Signal (12-lead, 10-s @ 500 Hz) + features (chest pain, hs-troponin I)
Cao *et al.* (80)	CNN-based 4-lead ECG model (lead-specific lightweight CNN; ML-Net)	2021	China	Retrospective	112 (MI 60; HC: 62)	MI *vs.* HC	4-lead (V2, V3, V5, aVL)	Signal (1-s segments @ 500 Hz)
Jian JZ *et al.* (81)	CNN-based ECG model (lead-branch narrow CNN; N-Net/multi-scale MSN-Net)	2021	Taiwan	Retrospective	200 patients/449 records (MI: 148/369; HC: 52/80)	MI *vs.* HC; localization	12-lead	Signal (beat-level @ 100 Hz)
Liu WC *et al.* (29)	CNN-based ECG model (82-layer Dense Attention; ECG12Net)	2021	Taiwan	Retrospective	77,799 (STEMI: 737; NSTEMI: 287)	STEMI *vs.* NSTEMI *vs.* non-AMI	12-lead	Signal (random 1,024-sample crops)
Liu W *et al.* (59)	CNN-based ECG model (GA-optimized multi-branch + lead-SE)	2021	China	Retrospective	PTB: 200 (MI: 148; HC: 52); PTB-XL: 18,885	MI *vs.* HC	12-lead	Signal
Wu L *et al.* (49)	Feature-based ECG model (LASSO logistic regression; 14 ECG features)	2022	Taiwan	Retrospective	268 (NSTEMI: 47; UA: 221)	NSTEMI *vs.* UA	12-lead	Features (ECG + clinical variables; auto-extracted)
Jahmunah V *et al.* (82)	CNN-based ECG model (DenseNet)	2022	Singapore	Retrospective	200 (MI: 148; HC: 52)	10 MI locations *vs.* HC	12-lead	Signal (beat-level, 651 samples per lead @ 1000 Hz)
Gibson CM *et al.* (83)	CNN-based ECG model (1D CNN)	2022	Latin America	Retrospective	8,511 ECGs (STEMI: 4,255; non-STEMI: 4,256)	STEMI *vs.* non-STEMI	Single lead (per lead models; best V2)	Signal (heartbeat, QRS-centered)
Choi YJ *et al.* (84)	CNN-based ECG image model (QCG; smartphone/PC photo)	2022	South Korea	Retrospective	187 (STEMI: 96)	STEMI *vs.* non-STEMI	12-lead	Image (printed/screen ECG; smartphone/screen-capture)
Fang R *et al.* (85)	CNN-based ECG image model (3D top-view, multi-VGG)	2022	Taiwan	Retrospective	PTB: 200 (MI: 148; HC: 52); PTB-XL: 8,776 (MI: 2,187; HC: 6,589)	MI *vs.* HC	12-lead	Image (3D top-view color images per heartbeat)
Shimizu M *et al.* (86)	Tree-ensemble on automated 12-lead ECG features	2022	Japan	Retrospective	112 (TTS: 56; anterior AMI: 56)	TTS *vs.* acute anterior MI	12-lead	ECG features + clinical variables
Kim D *et al.* (87)	CNN-based ECG image model (QCG)	2022	South Korea	Retrospective	80 (STEMI: 54)	STEMI *vs.* non-STEMI	12-lead	Image (ECG images)
Xiao R *et al.* (88)	Multimodal ECG + demographics model (1D xResNet feature fusion)	2022	USA	Retrospective	18,885 patients, 21,837 ECGs (MI: 5,486; non-MI: 16,351)	MI *vs.* non-MI	12-lead	Signal (1D ECG) + features (age/sex)
Wu L *et al.* (30)	CNN-LSTM-based ECG model	2022	China	Retrospective	883 (STEMI: 377; control: 506)	STEMI *vs.* control; culprit vessel	12-lead	Signal (5-s @ 1000 Hz)
Chen KW *et al.* (33)	CNN–LSTM–based ECG model (mini-12-lead device)	2022	Taiwan	Prospective	275 (362 prehospital ECGs)	STEMI *vs.* non-STEMI	12-lead (mini device; ambulance)	Signal
Tseng LM *et al.* (89)	CNN-based ECG model (2D time-frequency CNN; CWT/STFT-ResNet)	2022	Taiwan	Retrospective	384 STEMI (LAD: 208; LCX: 44; RCA: 132)	Culprit artery (LAD *vs.* LCX *vs.* RCA)	12-lead	Signal → 2D spectrogram images
Sraitih M *et al.* (90)	ML-based ECG model (SVM/KNN/RF on raw R-centered segments)	2022	Morocco; France	Retrospective	106 (MI: 53; HC: 53)	MI *vs.* HC	12-lead	Signal (0.65-s R-centered @ 1000 Hz, per lead)
Choi HY *et al.* (91)	CNN-based ECG model (shared-encoder 1D-ResNet; 4×2.5-s ensemble)	2022	South Korea	Retrospective	60,157 ECGs (STEMI: 117; NSR: 60,040)	STEMI *vs.* NSR	12-lead	Signal (10-s)
Gustafsson S *et al.* (43)	CNN-based 8-lead ECG model (1D ResNet ensemble)	2022	Sweden	Retrospective	214,250 (492,226 ECGs)	STEMI *vs.* NSTEMI *vs.* control	8-lead (I, II, V1–V6)	Signal (10-s @ 250-500 Hz) + demographics (age/sex)
Jahmunah V *et al.* (92)	CNN-based ECG model (DenseNet)	2023	Singapore	Retrospective	200 (MI: 148; HC: 52); 29,234 beats	10 MI locations *vs.* HC	12-lead (best: V6)	Signal (1D ECG beats)
Ramezani Moghadam S *et al.* (93)	Tree-ensemble model (RF) with morphological features	2023	Iran	Retrospective	165 (MI: 113; HC: 52)	MI *vs.* HC; localization	12-lead	Morphological features (intervals, amplitudes, angles)
Chauhan C *et al.* (94)	ML-based model with tensor features	2023	India	Retrospective	173 (MI: 100; HC: 73)	MI *vs.* HC; localization	12-lead	Signal (segments @ 1000 Hz)
Herman R *et al.* (52)	CNN-based 12-lead ECG model (lead-specific DCNN; PMcardio-OMI)	2023	Europe; USA	Retrospective	10,543 (development); 2,222 (test)	OMI *vs.* non-OMI	12-lead	Image (ECG images)
Qin L *et al.* (47)	XGBoost-based ML model (clinical + ECG features + labs)	2023	China	Retrospective	2,878 (NSTEMI: 1,409; UA: 1,469)	NSTEMI *vs.* UA	12-lead	Features (ECG + clinical variables)
de Capretz PO *et al.* (40)	CNN-based ECG + labs model (median-beat DCNN; CNN-MB)	2023	Sweden	Retrospective	9,519	AMI detection (secondary)	12-lead	Signal (median-beat ECG) + features (age/sex/labs)
Al-Zaiti SS *et al.* (64)	RF-based 12-lead ECG model (ECG-SMART; 73 engineered temporal-spatial features)	2023	USA	Prospective	7,313	OMI *vs.* non-OMI (no STEMI)	12-lead	ECG features (73 morphologic from 554 temporal–spatial metrics on median beats)
Xiao R *et al.* (95)	CNN-based ECG model (multimodal 1D xResNet + age/sex)	2023	USA	Retrospective	18,885	MI *vs.* non-MI	12-lead	Signal (12-lead, 10-s) + demographics (age/sex)
Lee SH *et al.* (58)	CNN-based ECG model (deep ensemble of 5 CNNs)	2024	South Korea	Retrospective	– (18,697 ECGs; STEMI: 9.3%)	STEMI *vs.* non-STEMI	8-lead (I, II, V1–V6)	Signal (10-s @ 500 Hz)
Wang J *et al.* (38)	CNN-RNN-based ECG model with state refinement	2024	China	Retrospective	200 (MI: 148; HC: 52)	MI *vs.* HC	3-lead (II, III, V2)	Signal (2-s episodes @ 250 Hz)
Qiang Y *et al.* (36)	CNN-based ECG model with multi-channel dense attention	2024	China	Retrospective	165 (MI: 113; HC: 52)	MI *vs.* HC; localization	12-lead	Signal (heartbeats @ 500 Hz, per lead, 12 parallel channels; no denoising; z-score)
Lee SH *et al.* (96)	CNN-based ECG image model (qSTEMI biomarker; QCG)	2024	South Korea	Retrospective	53 (STEMI: 24)	STEMI *vs.* non-STEMI	12-lead	Image (ECG images)
Davarmanesh P *et al.* (97)	CNN-based ECG model (1D ResNet)	2024	USA	Retrospective	– (PTB-XL records used)	MI *vs.* HC	Single lead (I)	Signal (1D ECG)
Kim J *et al.* (35)	CNN-based ECG image model (Faster R-CNN STE detector + tabular ensemble)	2024	South Korea	Retrospective	888 MI (STEMI: 677; NSTEMI: 211)	STEMI *vs.* NSTEMI; territory (anterior/lateral/inferior/LM)	12-lead	Image (ECG scans) → features
Park MJ *et al.* (98)	CNN-based ECG image model (printed-ECG encoders; QCG™ qSTEMI)	2024	South Korea	Retrospective	58 (post-ROSC OHCA)	ACO *vs.* no occlusion	12-lead	Image (printed-ECG images)
Qu J *et al.* (37)	Shapelet-based ECG model (VCG → CDG dynamic learning; K-means + Softmin; ensemble)	2024	China	Retrospective	200 (MI: 148; HC: 52)	MI *vs.* HC	12-lead	Signal (12-lead ECG → 3-lead VCG: X, Y, Z)
Sheth KA *et al.* (61)	CNN-based ECG model (DWT-denoised 1D-CNN)	2024	India; South Korea	Retrospective	PTB-XL: 18,869 (21,799 records); PTB: 200 (MI: 148; HC: 52)	MI *vs.* HC	12-lead	Signal (10-s → DWT denoising)
Wang L *et al.* (99)	Multimodal ECG + labs model (1D ResNet + RF)	2025	China	Retrospective (learning) + prospective (test)	277 (AMI: 141; AAD-A: 136); prospective test: 62 (AMI: 30; AAD-A: 32)	AAD-Type A *vs.* AMI	8-lead (I, II, V1–V6)	Signal (10-s @ 1000 Hz) + features (labs/demographics)
Hori K *et al.* (47)	CNN-based ECG model (residual CNN)	2025	Japan	Retrospective	32,167 (ACS: 785; non-ACS: 31,382)	ACS (UA/NSTEMI/STEMI) *vs.* non-ACS	8-lead (I, II, V1–V6)	Signal (10-s @ 500 Hz)
Choi J *et al.* (2)	CNN-based ECG image model (QCG)	2025	South Korea	Retrospective (ad hoc analysis)	71 (ACS-O+: 44; ACS-O–: 12; control: 15)	ACS (± occlusion) *vs.* control	12-lead + 9-lead smartwatch (I, II, III, V1–V6; asynchronous)	Image (ECG images)
Chen Y *et al.* (60)	Multi-domain feature fusion CNN model (1D signal + 2D GAF/ST)	2025	China	Retrospective	PTB: 179 (MI: 127; HC: 52); PTB-XL (external test)	MI detection; localization	12-lead	Signal (1D ECG) + 2D spectrum (GAF) + 2D time-frequency (S-transform)
Lee H *et al.* (100)	CNN-based ECG image model (ECG Buddy; STEMI biomarker)	2025	South Korea	Retrospective	928 ECG images	MI *vs.* non-MI	12-lead	Image (ECG images)
Ahuja Y *et al.* (41)	CNN-based ECG model (1D ResNet)	2025	USA	Retrospective	123,397	Coronary revascularization (PCI/CABG)	12-lead	Signal (10-s @ 250 Hz)
Meyers HP *et al.* (101)	CNN-based ECG model (PMcardio)	2025	USA	Retrospective	808 ACS (LAD TIMI-0: 53)	LAD OMI (TIMI-0)	12-lead	Image (ECG images)
Park BE *et al.* (44)	CNN-based ECG image model (signal-guided multitask; U-Net + SE-ResNet)	2025	South Korea	Retrospective	– (11,227 ECG images; MI: 3,003; non-MI: 8,224)	MI *vs.* non-MI	12-lead	Image (ECG images + signal-derived mask)
Díaz-Herrera BA *et al.* (102)	CNN-based ECG image model (InceptionResNetV2 transfer-learning)	2025	Mexico	Prospective	362	ACOMI *vs.* non-ACOMI	12-lead	Image (ECG images, smartphone photo, 256×256)
Choi JWH *et al.* (103)	CNN-based ECG model (PMcardio)	2025	USA	Retrospective	217	OMI *vs.* NOMI in ACS	12-lead	Image (ECG images)
Goktekin *et al.* (34)	MI-MS ConvMixer + WSSE (ConvMixer + SVM ensemble)	2025	Türkiye	Retrospective	1,321	NSTEMI culprit coronary artery (7-class: LAD/LCx/RCA/combinations)	12-lead	Signal → 2D spectrogram images per lead
Janciuleviciute K *et al.* (104)	CNN-based wrist-ECG model (1D-CNN on averaged beats; 4-lead)	2025	Lithuania	Prospective	123 (AMI: 52; HC: 51; other diseases: 20)	AMI *vs.* non-AMI	Wrist-worn device (2-4 leads)	Signal (average-beat)
Riek NT *et al.* (105)	CNN-based ECG model (temporal → spatial ResNet)	2025	USA	Retrospective	7,397 (10,393 ECGs)	OMI *vs.* non-OMI	12-lead	Signal (12-lead @ 250 Hz)
Lee MS *et al.* (63)	CNN-based ECG model (residual DCNN; AiTiAMI)	2025	South Korea	Prospective	8,493 (ED chest pain; AMI: 18.6%)	AMI (type 1/2) detection	12-lead	Signal (12-lead @ 500 Hz)
Krychtiuk KA *et al.* (57)	CNN-based ECG model (InceptionTime 1D-CNN)	2025	USA	Retrospective	ED visits: 144,691 (train), 35,995 (test); 18,673 (external)	Coronary revascularization; type 1 MI (external)	12-lead	Signal (10-s @ 100 Hz)
Demandt JPA *et al.* (106)	CNN-based ECG model (median-beat)	2025	Netherlands	Retrospective (development); prospective (external validation)	Development: 4,891 (NSTE-ACS: 25%); external: 754 (NSTE-ACS: 27%)	NSTE-ACS *vs.* non-cardiac chest pain	12-lead	Signal (10-s @ 5000 Hz, median-beat per lead)
Gadag V *et al.* (45)	CNN-based ECG image model (Siamese twin CNN; SNN-ECG)	2025	India; South Korea	Retrospective	– (928 images)	MI *vs.* abnormal heartbeat *vs.* normal	12-lead	Image (ECG images, 256×256)
Yang X *et al.* (39)	Graph-based ECG model (MDD2DG-IRA: visibility-graph degree dists → ViT-IRA + GCN)	2025	China	Retrospective	PTB: 180; PTB-XL: 9,571	MI *vs.* HC; localization	12-lead	Signal → visibility graph (degree distributions → graph features)
Pon Bharathi A *et al.* (62)	ResNet-based ECG model (SSS-optimized DRN; engineered feature fusion)	2025	India	Retrospective	PTB: 290 (MI: 148); MIT-BIH: 48	MI *vs.* non-MI	12-lead	Features (multiple-kernel MFCC + Haar/DWT + R/QT/RR/PR/PP)
Ashokan PL *et al.* (31)	Hybrid ECG model (CNNBoost: XGBoost + 1D-CNN; image → signal)	2025	India	Retrospective	– (928 images)	Normal *vs.* abnormal *vs.* MI *vs.* previous MI	12-lead	Signal (per lead 1D time series from images) + CNN spatial features
Bulbul AAM *et al.* (32)	CNN-based 4/12-lead ECG model (Inception + Attention; lead-optimized II–V2–V3–V5; "CardIA-Net")	2025	Australia; Bangladesh; Saudi Arabia	Retrospective	CSN: 10,646; PTB: 290	MI *vs.* non-MI *vs.* HC	12-lead (optimal 4-lead: II, V2, V3, V5)	Signal (0.6-s R-centered @ 500 Hz)
Büscher A *et al.* (107)	CNN-based ECG model	2025	USA	Retrospective	180,686 (development); 18,673 (external)	Coronary revascularization (PCI or CABG)	12-lead	Signal

AAD-A, acute aortic dissection type A; ACS, acute coronary syndrome; ACS-O+, acute coronary syndrome with occlusion; ACS-O–, acute coronary syndrome without occlusion; ACO, acute coronary occlusion; ACOMI, acute coronary occlusion myocardial infarction; ALMI, anterolateral myocardial infarction; AMI, acute myocardial infarction; ASMI, anteroseptal myocardial infarction; ANN, artificial neural network; BLSTM, bidirectional long short-term memory; CABG, coronary artery bypass grafting; CAD, coronary artery disease; CDG, cardiodynamicsgram; CHF, congestive heart failure; CNN, convolutional neural network; CSN, Chapman-Shaoxing-Ningbo ECG database; CWT, continuous wavelet transform; DCNN, deep convolutional neural network; DLA, deep layer aggregation; DRN, deep residual network; DWT, discrete wavelet transform; ECG, electrocardiography; ED, emergency department; FDM, Fourier decomposition method; FFPSO, fitness-based firefly particle swarm optimization; FIBF, Fourier Intrinsic Band Function; GAF, Gramian angular field; GAMI, generalized acute myocardial infarction; GBM, gradient boosting machine; GCN, graph convolutional network; GOA, grasshopper optimization algorithm; HC, healthy control; hs-TnI, high-sensitivity troponin I; ILMI, inferolateral myocardial infarction; IMI, inferior myocardial infarction; kNN, k-nearest neighbors; LAD, left anterior descending artery; LASSO, least absolute shrinkage and selection operator; LCx, left circumflex artery; LM, left main; LR, logistic regression; LSTM, long short-term memory; MFCC, mel-frequency cepstral coefficients; MI, myocardial infarction; ML, machine learning; NOMI, non-occlusion myocardial infarction; NSR, normal sinus rhythm; NSTE-ACS, non-ST-elevation acute coronary syndrome; NSTEMI, non-ST-elevation myocardial infarction; OHCA, out-of-hospital cardiac arrest; OMI, occlusion myocardial infarction; PCA, principal component analysis; PCI, percutaneous coronary intervention; QCG, Quantitative ECG; RBF, radial basis function; RCA, right coronary artery; RF, random forest; RNN, recurrent neural network; ROSC, return of spontaneous circulation; SE, squeeze-and-excitation; SNN, Siamese neural network; SSS, social ski-spider optimization; ST, S-transform; STE, ST-segment elevation; STEMI, ST-elevation myocardial infarction; STFT, short-time Fourier transform; SVM, support vector machine; SWT, stationary wavelet transform; TIMI, thrombolysis in myocardial infarction; TTS, Takotsubo syndrome; UA, unstable angina; VAE, variational autoencoder; VCG, vectorcardiogram; ViT, vision transformer; VMD, variational mode decomposition; WSSE, weighted subspace SVM ensemble.

Table S3 Performance metrics and validation characteristics of AI models for myocardial infarction detection

Author	Year	Public dataset (Y/N)	Patient data (Y/N)	AUROC	Sensitivity (%)	Specificity (%)	Reference	External validation (Y/N)
Kora P. (11)	2017	Y	N	–	100.0	98.7	Public dataset labels	N
Liu W *et al.* (14)	2018	Y	N	0.996	98.7	99.4	Public dataset labels	N
Sopic D *et al.* (12)	2018	Y	N	–	88.0	78.8	Public dataset labels	N
Liu W *et al.* (65)	2018	Y	N	–	95.4	97.4	Public dataset labels	N
Wu CC *et al.* (48)	2019	N	Y	0.984	90.9	93.3	Clinician diagnosis using ICD-9CM codes	N
Wang HM *et al.* (22)	2019	Y	N	0.979	98.4	97.5	Public dataset labels	N
Strodthoff N *et al.* (66)	2019	Y	N	–	93.3	89.7	Public dataset labels	N
Wang Z *et al.* (67)	2020	Y	N	–	73.9	97.7	Public dataset labels	N
Zhao Y *et al.* (42)	2020	N	Y	0.995	96.8	99.2	CAG	Y—independent institutional cohort
Han C *et al.* (68)	2020	Y	N	0.980	94.9	97.4	Public dataset labels	N
Hao P *et al.* (69)	2020	N	Y	–	96.4	95.9	Cardiologist-labeled ECG images	N
Zeng W *et al.* (70)	2020	Y	N	–	98.1	97.4	Public dataset labels	N
Sharma LD *et al.* (71)	2020	Y	N	0.990	98.6	99.4	Public dataset labels	N
Kapfo A *et al.* (72)	2020	N	Y	–	99.9	99.9	Public dataset labels	N
Liu W *et al.* (24)	2020	Y	N	–	94.4	86.3	Public dataset labels	N
Al-Zaiti S *et al.* (23)	2020	N	Y	0.820	77.0	76.0	4th UDMI	Y—prospective temporal validation
Makimoto H *et al.* (73)	2020	Y	N	0.880	86.0	76.0	Public dataset labels	N
Cho Y *et al.* (56)	2020	N	Y	0.901	84.4	88.5	CAG	Y—independent institutional cohort
Fu L *et al.* (25)	2020	Y	N	–	97.1	93.3	Public dataset labels	N
Martínez-Sellés M *et al.* (74)	2021	N	Y	–	–	–	CAG, troponin; 4th UDMI	Y—prospective multicenter validation
Jahmunah V *et al.* (75)	2021	Y	N	–	98.7	99.5	Public dataset labels	N
Martin H *et al.* (19)	2021	Y	N	0.880	75.9	83.0	Public dataset labels	Y—cross-database (trained on PTB-XL → tested on PTB)
Xiong P *et al.* (76)	2021	Y	N	–	99.8	100.0	Public dataset labels	N
He Z *et al.* (15)	2021	Y	N	–	96.9	96.9	Public dataset labels	Y—cross-database
Tadesse GA *et al.* (27)	2021	Y	Y	0.852	67.6	83.3	Cardiologist adjudication from hospital records + ECG; onset-time labels	N
Fatimah B *et al.* (77)	2021	Y	N	–	100.0	100.0	Public dataset labels	N
Martin H *et al.* (18)	2021	Y	N	–	91.9	80.8	Public dataset labels	N
Safdarian N *et al.* (78)	2021	Y	N	–	100.0	100.0	Public dataset labels	N
Mahmoudinejad SA *et al.* (79)	2021	Y	N	–	94.9	86.4	Public dataset labels	N
Han C *et al.* (26)	2021	N	Y	0.880	71.8	86.6	ICD-10 discharge diagnosis	N
Liu WC *et al.* (28)	2021	N	Y	STEMI 0.996–0.999; NSTEMI 0.991	STEMI 93.2; NSTEMI 62.1	NSTEMI 100.0; STEMI –	CAG, troponin	Y—prospective temporal validation
Cao *et al.* (80)	2021	Y	N	–	94.3	97.7	Public dataset labels	N
Jian JZ *et al.* (81)	2021	Y	N	–	–	–	Public dataset labels	N
Liu WC *et al.* (29)	2021	N	Y	STEMI 0.997	STEMI 98.4	STEMI 96.9	Positive AMI adjudicated by three interventional cardiologists per guidelines	N
Liu W *et al.* (59)	2021	Y	N	–	98.5	90.0	Public dataset labels	Y—cross-database (trained on PTB → tested on PTB-XL)
Wu L *et al.* (49)	2022	N	Y	0.940	85.0	86.0	Physician diagnosis	Y—independent institutional cohort
Jahmunah V *et al.* (82)	2022	Y	N	–	–	–	Public dataset labels	N
Gibson CM *et al.* (83)	2022	N	Y	–	96.3	96.8	STEMI criteria as guidelines	Y—independent institutional cohort
Choi YJ *et al.* (84)	2022	N	Y	0.839	85.4	82.4	EMR review of clinical data (including CAG and echocardiography)	Y—independent institutional cohort
Fang R *et al.* (85)	2022	Y	N	0.986-0.996	95.6-97.3	90.8-97.9	Public dataset labels	N
Shimizu M *et al.* (86)	2022	N	Y	0.865–0.881	83.0–87.0	–	Mayo criteria (TTS); 4th UDMI (AMI); CAG	N
Kim D *et al.* (87)	2022	N	Y	0.947	98.1	76.9	EMR adjudication including CAG/ echocardiography	N
Xiao R *et al.* (88)	2022	Y	N	0.921	69.7	93.4	Public dataset labels	N
Wu L *et al.* (30)	2022	N	Y	0.990	94.0	83.0	CAG; 4th UDMI	Y—independent external cohort (n=90) from another hospital
Chen KW *et al.* (33)	2022	N	Y	0.997	94.1	99.4	Cardiologist consensus (ECG-based)	Y—independent institutional cohort
Tseng LM *et al.* (89)	2022	N	Y	–	LAD 93.46; LCX 56.0; RCA 85.9	LAD 80.39; LCX 99.7; RCA 92.9	CAG	N
Sraitih M *et al.* (90)	2022	Y	N	–	73.0	77.0	Public dataset labels	N
Choi HY *et al.* (91)	2022	N	Y	0.998	97.4	99.2	CAG; 4th UDMI	Y—external test of a pre-trained DLM
Gustafsson S *et al.* (43)	2022	N	Y	STEMI/NSTEMI 0.985-0.991/0.832-0.867	–	–	SWEDEHEART registry discharge diagnosis	Y—temporal split within cohort + PTB-XL STEMI subset
Jahmunah V *et al.* (92)	2023	Y	N	–	–	–	Public dataset labels	N
Ramezani Moghadam S *et al.* (93)	2023	Y	N	–	99.7	83.6	Public dataset labels	N
Chauhan C *et al.* (94)	2023	Y	N	–	98.0	100.0	Public dataset labels	N
Herman R *et al.* (52)	2023	N	Y	0.941	82.6	92.8	CAG, troponin	Y—independent US external test set
Qin L *et al.* (47)	2023	N	Y	0.970	98.0	–	2020 ESC NSTE-ACS guideline; troponin, ECG, echocardiography, and CAG	Y—trained on one center → tested on the other center
de Capretz PO *et al.* (40)	2023	N	Y	0.939	99.5	98.5	3rd UDMI	N
Al-Zaiti SS *et al.* (64)	2023	N	Y	0.870	86.0	98.0	CAG, troponin	Y—two independent external sites
Xiao R *et al.* (95)	2023	Y	N	0.921	69.7	93.4	Public dataset labels	N
Lee SH *et al.* (58)	2024	Y	Y	0.978-0.979	83.3-95.0	89.1-97.9	Guidelines, CAG	Y—tested on PTB-XL
Wang J *et al.* (38)	2024	Y	N	–	99.0–99.1	99.1–99.2	Public dataset labels	N
Qiang Y *et al.* (36)	2024	Y	N	–	97.2	97.2	Public dataset labels	N
Lee SH *et al.* (96)	2024	N	Y	0.815	75.0	86.2	Final hospital final diagnosis	Y—independent institutional cohort
Davarmanesh P *et al.* (97)	2024	Y	N	0.950	86.0	85.0	Public dataset labels	N
Kim J *et al.* (35)	2024	N	Y	0.939	89.4	89.7	Clinical records by physicians	N
Park MJ *et al.* (98)	2024	N	Y	0.770	70.8	79.4	CAG	Y—independent institutional cohort
Qu J *et al.* (37)	2024	Y	N	0.935	95.0	91.0	Public dataset labels	N
Sheth KA *et al.* (61)	2024	Y	N	0.980	94.0	–	Public dataset labels	Y—cross-database (trained on PTB-XL → tested on PTB)
Wang L *et al.* (99)	2025	N	Y	0.968	96.9	96.7	AAD-A: CTA; AMI: 4th UDMI	Y—prospective temporal hold-out (same center)
Hori K *et al.* (46)	2025	N	Y	0.889	76.0-80.0	82.0-83.0	Cardiologist adjudication per ACC/AHA criteria; troponin-T, echocardiography, CAG/CTA	N
Choi J *et al.* (2)	2025	N	Y	0.991	–	–	CAG, troponin	Y—independent cohort (Italy)
Chen Y *et al.* (60)	2025	Y	N	–	100.0	74.9	Public dataset labels	Y—cross-database (trained on PTB → tested on PTB-XL)
Lee H *et al.* (100)	2025	Y	N	0.989	96.7	97.1	Public dataset labels	Y—independent institutional cohort
Ahuja Y *et al.* (41)	2025	N	Y	0.67-0.91	–	–	Coronary revascularization	N
Meyers HP *et al.* (101)	2025	N	Y	–	100.0	–	CAG	N
Park BE *et al.* (44)	2025	N	Y	0.959	83.8	93.0	Lab, CAG, echocardiography	N
Díaz-Herrera BA *et al.* (102)	2025	N	Y	0.860	100.0	73.3	CAG; 4th UDMI	N
Choi JWH *et al.* (103)	2025	N	Y	0.840	86.5	82.2	CAG, troponin	Y—independent institutional cohort
Goktekin *et al.* (34)	2025	N	Y	–	89.1	98.1	CAG	N
Janciuleviciute K *et al.* (104)	2025	Y	Y	–	77.0	75.0	Public dataset labels (training); clinical AMI diagnosis (test)	Y—trained on PTB-XL → tested on independent wrist-ECG cohort (Lithuania)
Riek NT *et al.* (105)	2025	N	Y	0.953	67.7	99.6	CAG	N
Lee MS *et al.* (63)	2025	N	Y	0.878	76.7	84.8	4th UDMI	Y—prospective, multicenter sites independent of training data
Krychtiuk KA *et al.* (57)	2025	Y	Y	0.810-0.910	–	–	Coronary revascularization; 4th UDMI	Y—independent external cohort (Germany)
Demandt JPA *et al.* (106)	2025	N	Y	0.700	80.3	89.8	ESC guidelines, 4th UDMI	Y—prospective prehospital multicenter cohort (n=754)
Gadag V *et al.* (45)	2025	Y	N	–	95.0	91.0	Public dataset labels	N
Yang X *et al.* (39)	2025	Y	N	–	–	–	Public dataset labels	Y—evaluated on both PTB and PTB-XL datasets
Pon Bharathi A *et al.* (62)	2025	Y	N	–	92.1	92.6	Public dataset labels	N
Ashokan PL *et al.* (31)	2025	Y	N	0.988	93.8	–	Dataset expert annotations per Telehealth ECG diagnostic system	N
Bulbul AAM *et al.* (32)	2025	Y	N	Normal 0.985; MI 0.999; non-MI 0.984	98.8	99.1	Public dataset labels	N
Büscher A *et al.* (107)	2025	Y	Y	0.810-0.910	79.8	–	Coronary revascularization	Y—German single-center ED cohort (non-STEMI), low/ intermediate/high-risk allocation

AAD-A, acute aortic dissection type A; ACC, American College of Cardiology; ACS, acute coronary syndrome; AHA, American Heart Association; AMI, acute myocardial infarction; AUROC, area under the receiver operating characteristic curve; CAG, coronary angiography; CTA, computed tomography angiography; DLM, deep-learning model; ECG, electrocardiography; ED, emergency department; EMR, electronic medical record; ESC, European Society of Cardiology; ICD, International Classification of Diseases; LAD, left anterior descending artery; LCX, left circumflex artery; MIT-BIH, Massachusetts Institute of Technology-Beth Israel Hospital database; NSTE-ACS, non-ST-elevation acute coronary syndrome; NSTEMI, non-ST-elevation myocardial infarction; OMI, occlusion myocardial infarction; PTB, Physikalisch-Technische Bundesanstalt database; PTB-XL, Physikalisch-Technische Bundesanstalt extra-large database; RCA, right coronary artery; STEMI, ST-elevation myocardial infarction; SWEDEHEART, Swedish Web-system for Enhancement and Development of Evidence-based care in Heart disease Evaluated According to Recommended Therapies; TTS, Takotsubo syndrome; UDMI, Universal Definition of Myocardial Infarction.

Table S4 Summary of OMI-focused studies: definition, validation type, and reported PPV/NPV

First author (year)	OMI definition (TIMI criteria)	Validation type	PPV (%)	NPV (%)	Threshold prespecified (Y/N)	Intended use
Martínez-Sellés *et al.* (2021)	TIMI 0–1	Prospective MC	NR	NR	NR	NR
Herman *et al.* (2023)	TIMI 0-2; or TIMI 3 + very high peak Tn	External cohort	74.1	95.5	Y	Rule-in (triage)
Al-Zaiti *et al.* (2023)	TIMI 0–1; or TIMI 2 + >70% stenosis + Tn	Prospective MC	54.0	99.0	NR	Dual (rule-in/out)
Park *et al.* (2024)	Angiography-adjudicated	External cohort	70.8	79.4	NR	Rule-in (triage)
Riek *et al.* (2025)	TIMI 0–1; or TIMI 2 + >70% stenosis + Tn	Internal only	93.3	97.1	Y	Dual (rule-in/out)
Choi *et al.* (2025)	TIMI 0–2; or TIMI 3 + peak TnI ≥10 ng/mL	External cohort	81.1	87.4	NR	Rule-in (triage)
Meyers *et al.* (2025)	TIMI 0 only (total occlusion)	Internal only	NR	NR	NR	NR
Díaz-Herrera *et al.* (2025)	Total occlusion; or thrombus ≥2 + flow ≤1; or >95% stenosis	Internal only	84.6	100.0	NR	Rule-in (triage)
Goktekin *et al.* (2025)	Angiography-adjudicated	Internal only	NR	NR	NR	NR

OMI definition summarizes the angiographic criteria (TIMI flow grade, anatomic severity, and/or biomarker thresholds) used to operationalize occlusion myocardial infarction in each study. Where angiographic adjudication was performed but specific TIMI flow or stenosis criteria were not reported, the definition is listed as “angiography-adjudicated”. PPV and NPV values are reported as presented in the original studies at the authors’ selected operating point(s). Because PPV and NPV are prevalence-dependent and operating thresholds were not consistently prespecified or reported across studies, these values should be interpreted as descriptive rather than directly comparable. Threshold prespecified indicates whether the decision threshold was defined a priori versus selected post hoc; if not stated, it is marked NR. Validation type follows our five-tier taxonomy described in the Methods: internal only (single-dataset evaluation without independent testing), cross-database, external cohort (independent institutional cohort), prospective temporal (temporally separated validation), and prospective multicenter (prospective validation across geographically distinct sites). AI, artificial intelligence; ECG, electrocardiogram; MC, multicenter; NPV, negative predictive value; OMI, occlusion myocardial infarction; PPV, positive predictive value; TIMI, thrombolysis in myocardial infarction; Tn, troponin; TnI, troponin I; NR, not reported.

References

68. Han C, Shi L. ML-ResNet: A novel network to detect and locate myocardial infarction using 12 leads ECG. Comput Methods Programs Biomed. 2020;185:105138.
69. Hao P, Gao X, Li Z, Zhang J, Wu F, Bai C. Multi-branch fusion network for Myocardial infarction screening from 12-lead ECG images. Comput Methods Programs Biomed. 2020;184:105286.
70. Zeng W, Yuan J, Yuan C, Wang Q, Liu F, Wang Y. Classification of myocardial infarction based on hybrid feature extraction and artificial intelligence tools by adopting tunable-Q wavelet transform (TQWT), variational mode decomposition (VMD) and neural networks. Artif Intell Med. 2020;106:101848.
71. Sharma LD, Sunkaria RK. Myocardial Infarction Detection and Localization Using Optimal Features Based Lead Specific Approach. Irbm. 2020;41(1):58-70.
72. Kapfo A, Dandapat S, Kumar Bora P. Automated detection of myocardial infarction from ECG signal using variational mode decomposition based analysis. Healthcare Technology Letters. 2020;7(6):155-60.
73. Makimoto H, Hockmann M, Lin T, Glockner D, Gerguri S, Clasen L, et al. Performance of a convolutional neural network derived from an ECG database in recognizing myocardial infarction. Sci Rep. 2020;10(1):8445.
74. Martinez-Selles M, Juarez M, Marina-Breysse M, Lillo-Castellano JM, Ariza A. Rational and design of ST-segment elevation not associated with acute cardiac necrosis (LESTONNAC). A prospective registry for validation of a deep learning system assisted by artificial intelligence. J Electrocardiol. 2021;69:140-4.

75. Jahmunah V, Ng EYK, San TR, Acharya UR. Automated detection of coronary artery disease, myocardial infarction and congestive heart failure using GaborCNN model with ECG signals. Comput Biol Med. 2021;134:104457.
76. Xiong P, Xue Y, Zhang J, Liu M, Du H, Zhang H, et al. Localization of myocardial infarction with multi-lead ECG based on DenseNet. Comput Methods Programs Biomed. 2021;203:106024.
77. Fatimah B, Singh P, Singhal A, Pramanick D, S P, Pachori RB. Efficient detection of myocardial infarction from single lead ECG signal. Biomedical Signal Processing and Control. 2021;68.
78. Safdarian N, Nezhad SYD, Dabanloo NJ. Detection and Classification of Myocardial Infarction with Support Vector Machine Classifier Using Grasshopper Optimization Algorithm. J Med Signals Sens. 2021;11(3):185-93.
79. Mahmoudinejad SA, Safdarian N. Evaluating Morphological Features of Electrocardiogram Signals for Diagnosing of Myocardial Infarction Using Classification-Based Feature Selection. J Med Signals Sens. 2021;11(2):79-91.
80. Cao Y, Wei T, Zhang B, Lin N, Rodrigues J, Li J, et al. ML-Net: Multi-Channel Lightweight Network for Detecting Myocardial Infarction. IEEE J Biomed Health Inform. 2021;25(10):3721-31.
81. Jian JZ, Ger TR, Lai HH, Ku CM, Chen CA, Abu PAR, et al. Detection of Myocardial Infarction Using ECG and Multi-Scale Feature Concatenate. Sensors (Basel). 2021;21(5).
82. Jahmunah V, Ng EYK, Tan RS, Oh SL, Acharya UR. Explainable detection of myocardial infarction using deep learning models with Grad-CAM technique on ECG signals. Comput Biol Med. 2022;146:105550.
83. Gibson CM, Mehta S, Ceschim MRS, Frauenfelder A, Vieira D, Botelho R, et al. Evolution of single-lead ECG for STEMI detection using a deep learning approach. Int J Cardiol. 2022;346:47-52.
84. Choi YJ, Park MJ, Ko Y, Soh MS, Kim HM, Kim CH, et al. Artificial intelligence versus physicians on interpretation of printed ECG images: Diagnostic performance of ST-elevation myocardial infarction on electrocardiography. Int J Cardiol. 2022;363:6-10.
85. Fang R, Lu CC, Chuang CT, Chang WH. A visually interpretable detection method combines 3-D ECG with a multi-VGG neural network for myocardial infarction identification. Comput Methods Programs Biomed. 2022;219:106762.
86. Shimizu M, Suzuki M, Fujii H, Kimura S, Nishizaki M, Sasano T. Machine learning of microvolt-level 12-lead electrocardiogram can help distinguish takotsubo syndrome and acute anterior myocardial infarction. Cardiovasc Digit Health J. 2022;3(4):179-88.
87. Kim D, Hwang JE, Cho Y, Cho HW, Lee W, Lee JH, et al. A Retrospective Clinical Evaluation of an Artificial Intelligence Screening Method for Early Detection of STEMI in the Emergency Department. J Korean Med Sci. 2022;37(10):e81.
88. Xiao R, Ding C, Hu X, Zègre-Hemsey J. ML for MI - Integrating Multimodal Information in Machine Learning for Predicting Acute Myocardial Infarction. medRxiv. 2022:2022.10.25.22281536.
89. Tseng LM, Chuang CY, Chua SK, Tseng VS. Identification of Coronary Culprit Lesion in ST Elevation Myocardial Infarction by Using Deep Learning. IEEE J Transl Eng Health Med. 2023;11:70-9.
90. Sraitih M, Jabrane Y, Hajjam El Hassani A. A Robustness Evaluation of Machine Learning Algorithms for ECG Myocardial Infarction Detection. J Clin Med. 2022;11(17).
91. Choi HY, Kim W, Kang GH, Jang YS, Lee Y, Kim JG, et al. Diagnostic Accuracy of the Deep Learning Model for the Detection of ST Elevation Myocardial Infarction on Electrocardiogram. J Pers Med. 2022;12(3).
92. Jahmunah V, Ng EYK, Tan RS, Oh SL, Acharya UR. Uncertainty quantification in DenseNet model using myocardial infarction ECG signals. Comput Methods Programs Biomed. 2023;229:107308.
93. Ramezani Moghadam S, Asl BM. Automatic diagnosis and localization of myocardial infarction using morphological features of ECG signal. Biomedical Signal Processing and Control. 2023;83.
94. Chauhan C, Tripathy RK, Agrawal M. Patient specific higher order tensor based approach for the detection and localization of myocardial infarction using 12-lead ECG. Biomedical Signal Processing and Control. 2023;83.
95. Xiao R, Ding C, Hu X, Clifford GD, Wright DW, Shah AJ, et al. Integrating multimodal information in machine learning for classifying acute myocardial infarction. Physiol Meas. 2023;44(4).
96. Lee SH, Hong WP, Kim J, Cho Y, Lee E. Smartphone AI vs. Medical Experts: A Comparative Study in Prehospital STEMI Diagnosis. Yonsei Med J. 2024;65(3):174-80.
97. Davarmanesh P, Lin Q, Tenison I, Jabbour G, Alam R. Detection of Acute Myocardial Infarction Using Deep Learning on Lead-I ECG Data. 2024.
98. Park MJ, Choi YJ, Shim M, Cho Y, Park J, Choi J, et al. Performance of ECG-Derived Digital Biomarker for Screening Coronary Occlusion in Resuscitated Out-of-Hospital Cardiac Arrest Patients: A Comparative Study between Artificial Intelligence and a

 https://dx.doi.org/10.21037/cdt-2025-aw-561

Group of Experts. J Clin Med. 2024;13(5).
99. Wang L, Wu H, Wu C, Shu L, Zhou D. A deep-learning system integrating electrocardiograms and laboratory indicators for diagnosing acute aortic dissection and acute myocardial infarction. Int J Cardiol. 2025;423:133008.
100. Lee H, Yoo S, Kim J, Cho Y, Suh D, Lee K. A Comparative Study of Predictive model (ECG Buddy) and ChatGPT-4o for Myocardial Infarction Diagnosis via ECG image Analysis: Performance, Accuracy, and Clinical Feasibility. medRxiv. 2025:2025.04.04.25325246.
101. Meyers HP, Sharkey SW, Herman R, de Alencar JN, Shroff GR, Frick WH, et al. Failure of standard contemporary ST-elevation myocardial infarction electrocardiogram criteria to reliably identify acute occlusion of the left anterior descending coronary artery. Eur Heart J Acute Cardiovasc Care. 2025;14(7):403-11.
102. Diaz-Herrera BA, Roman-Rangel E, Castro-Garcia CA, Sierra-Lara Martinez D, Gopar-Nieto R, Velez-Talavera KG, et al. Derivation of an artificial intelligence-based electrocardiographic model for the detection of acute coronary occlusive myocardial infarction. Arch Cardiol Mex. 2025;95(2):178-87..
103. Choi JWH, Torelli V, Silverman A, Diaz SS, Kong D, Vaish E, et al. AI-enhanced recognition of occlusions in acute coronary syndrome (AERO-ACS): a retrospective study. Coron Artery Dis. 2026;37(1):39-45.
104. Janciuleviciute K, Sokas D, Bacevicius J, Sornmo L, Petrenas A. ECG-Based Detection of Acute Myocardial Infarction Using a Wrist-Worn Device. IEEE Trans Biomed Eng. 2026;73(1):234-44.
105. Riek NT, Akcakaya M, Bouzid Z, Gokhale T, Helman SM, Kraevsky K, et al. ECG-SMART-NET: A Deep Learning Architecture for Precise ECG Diagnosis of Occlusion Myocardial Infarction. IEEE Trans Biomed Eng. 2025;72(12):3613-20.
106. Demandt JPA, Mast TP, van Beek KAJ, Koks A, Bastiaansen MCV, Tonino PAL, et al. Towards prehospital risk stratification using deep learning for ECG interpretation in suspected acute coronary syndrome. BMJ Health Care Inform. 2025;32(1).
107. Buscher A, Plagwitz L, Yildirim K, Brix TJ, Neuhaus P, Bickmann L, et al. Deep Learning Electrocardiogram Model for Risk Stratification of Coronary Revascularization Need in the Emergency Department. Eur Heart J. 2025.

 https://dx.doi.org/10.21037/cdt-2025-aw-561