

TOPICAL REVIEW

Application of artificial intelligence techniques for automated detection of myocardial infarction: a review

To cite this article: Javad Hassannataj Joloudari *et al* 2022 *Physiol. Meas.* **43** 08TR01

View the [article online](#) for updates and enhancements.

You may also like






- [Quantitative evaluation of the mineralization level of dental tissues by Raman spectroscopy](#)
B Coello, M López-Álvarez, M Rodríguez-Domínguez et al.
- [Explainable cross-task adaptive transfer learning for motor imagery EEG classification](#)
Minmin Miao, Zhong Yang, Hong Zeng et al.
- [Detection of motor imagery of swallow EEG signals based on the dual-tree complex wavelet transform and adaptive model selection](#)
Huijuan Yang, Cuntai Guan, Karen Sui Geok Chua et al.



TOPICAL REVIEW

Application of artificial intelligence techniques for automated detection of myocardial infarction: a review

RECEIVED
21 February 2022REVISED
13 June 2022ACCEPTED FOR PUBLICATION
8 July 2022PUBLISHED
3 August 2022

Javad Hassannataj Joloudari^{1,2,*} , Sanaz Mojriani³, Issa Nodehi⁴, Amir Mashmool⁵ , Zeynab Kiani Zadegan¹, Sahar Khanjani Shirkharkolaie³, Roohallah Alizadehsani⁶, Tahereh Tamadon¹, Samiyeh Khosravi¹, Mitra Akbari Kohnehshari⁷, Edris Hassannatajjeloudari⁸, Danial Sharifrazi⁹, Amir Mosavi^{10,16} , Hui Wen Loh¹¹ , Ru-San Tan^{12,13} and U Rajendra Acharya^{11,14,15} 

¹ Department of Computer Engineering, Faculty of Engineering, University of Birjand, Birjand, Iran

² Department of Computer Engineering, Amol Institute of Higher Education, Amol, Iran

³ Department of Information Technology Engineering, Mazandaran University of Science and Technology, Babol, Iran

⁴ Department of Computer Engineering, University of Qom, Qom, Iran

⁵ Dipartimento di Informatica, Bioingegneria, Robotica e Ingegneria dei Sistemi (DIBRIS), Università di Genova, Genova, Italy

⁶ Institute for Intelligent Systems Research and Innovation, Deakin University, Geelong, VIC 3216, Australia

⁷ Computer Engineering Department, Engineering Faculty, Bu-Ali Sina University, Hamedan, Iran

⁸ Department of Nursing, School of Nursing and Allied Medical Sciences, Maragheh Faculty of Medical Sciences, Maragheh, Iran

⁹ Department of Computer Engineering, Shiraz Branch, Islamic Azad University, Shiraz, Iran

¹⁰ John von Neumann Faculty of Informatics, Obuda University, 1034 Budapest, Hungary

¹¹ School of Science and Technology, Singapore University of Social Sciences, Singapore

¹² Department of Cardiology, National Heart Centre Singapore, Singapore

¹³ Duke-NUS Medical School, Singapore

¹⁴ Ngee Ann Polytechnic, Singapore, 599489, Singapore

¹⁵ Dept. of Biomedical Informatics and Medical Engineering, Asia University, Taichung, Taiwan

¹⁶ Institute of Information Engineering, Automation and Mathematics, Slovak University of Technology in Bratislava, Slovakia

* Author to whom any correspondence should be addressed.

E-mail: javad.hassannataj@birjand.ac.ir

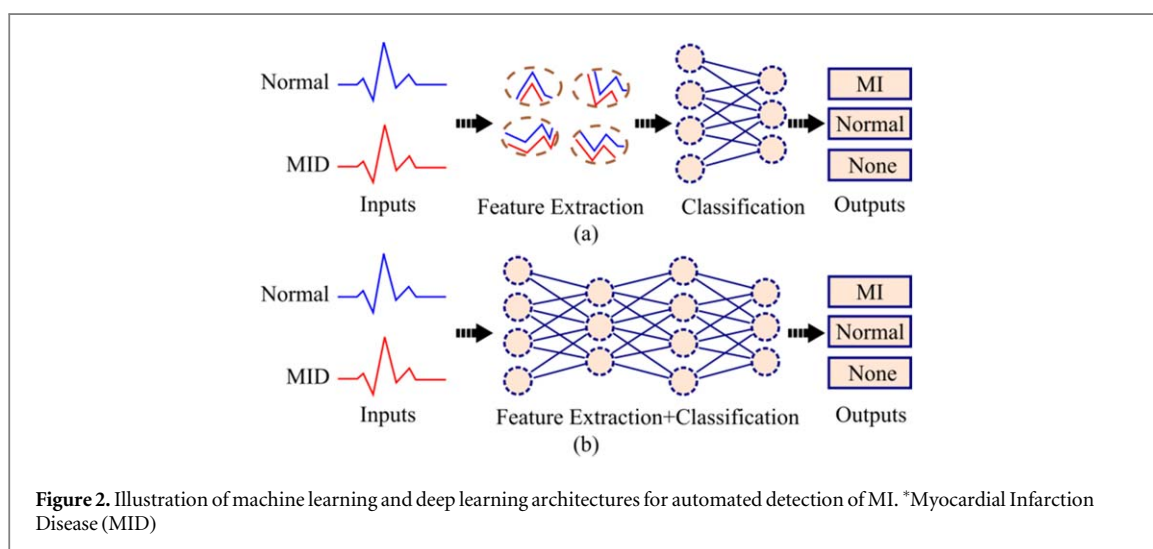
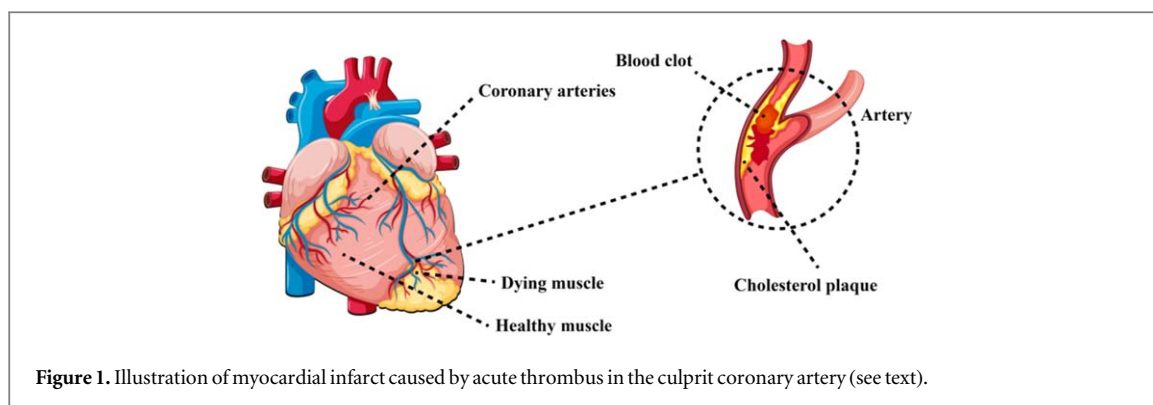
Keywords: deep convolutional neural network, deep learning, diagnosis, electrocardiogram, machine learning, myocardial infarction disease

Abstract

Objective. Myocardial infarction (MI) results in heart muscle injury due to receiving insufficient blood flow. MI is the most common cause of mortality in middle-aged and elderly individuals worldwide. To diagnose MI, clinicians need to interpret electrocardiography (ECG) signals, which requires expertise and is subject to observer bias. Artificial intelligence-based methods can be utilized to screen for or diagnose MI automatically using ECG signals. **Approach.** In this work, we conducted a comprehensive assessment of artificial intelligence-based approaches for MI detection based on ECG and some other biophysical signals, including machine learning (ML) and deep learning (DL) models. The performance of traditional ML methods relies on handcrafted features and manual selection of ECG signals, whereas DL models can automate these tasks. **Main results.** The review observed that deep convolutional neural networks (DCNNs) yielded excellent classification performance for MI diagnosis, which explains why they have become prevalent in recent years. **Significance.** To our knowledge, this is the first comprehensive survey of artificial intelligence techniques employed for MI diagnosis using ECG and some other biophysical signals.

1. Introduction

In myocardial infarction (MI), or heart attack, heart muscle cells die from lack of oxygen due to insufficient blood supply (Canto *et al* 2000, Boersma *et al* 2003, Jayachandran 2010, Sun *et al* 2012, Yang *et al* 2013). The latter is predominantly caused by coronary artery disease, in which the lumina of coronary arteries supplying the heart muscle become stenotic from atherosclerosis of the artery walls. In advanced coronary artery disease, the atherosclerotic plaque expands and becomes vulnerable to surface rupture (Creemers *et al* 2001), which can

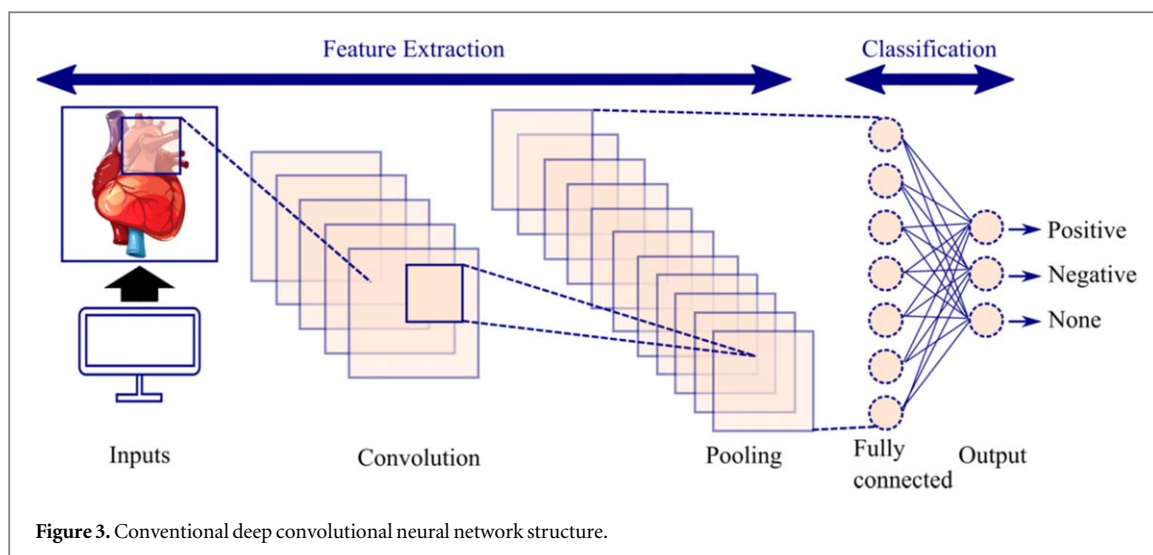


trigger the sudden formation of lumen-occluding thrombus, resulting in MI. This typical MI scenario is depicted in figure 1, where the death of a region of the heart muscle is caused by acute thrombus occlusion adjacent to a ruptured cholesterol-laden plaque at the site of coronary artery stenosis (inset).

After a MI, the left ventricle enlarges and undergoes functional changes in response to injury. This eventually leads to congestive heart failure, where the weakened heart muscle is unable to pump blood through the body efficiently, and at the advanced stage, death can ensue. Therefore, prompt diagnosis of MI and early intervention are critical for patients' survival. Electrocardiography (ECG) is the most common method used to diagnose MI (Banerjee and Mitra 2012, Liu *et al* 2015, Hammad *et al* 2021a). ECG is a surface map of the underlying cardiac action potentials during electrical signal conduction through the heart chambers. It will typically show abnormal morphology at lead positions overlying the involved MI region. The open-access Physikalisch-Technische Bundesanstalt (PTB) database is a repository of cardiologist-annotated ECGs of diverse cardiological conditions, including MI, which scientists frequently use for MI research (<https://physionet.org/content/ptbdb/1.0.0/>, (accessed 2022), Bousseljot *et al* 1995).

Other methods for diagnosing MI include noninvasive imaging, e.g. echocardiography and magnetic resonance imaging, and clinical and serological parameters. However, the manual interpretation of ECG, imaging readouts, and clinical parameters require expertise and may be subject to intra- and inter-observer variability. Artificial intelligence (AI)-enabled automated computer-aided diagnostic systems (Jiang *et al* 2017, Yu *et al* 2018, Davenport and Kalakota 2019, Ribeiro *et al* 2021) may improve efficiency and reduce observer bias in screening for MI using the different biological signals.

Both machine learning (ML) and deep learning (DL) models may be deployed for discriminating MI versus normal at the signal readout or subject levels. In ML (Mitchell 1997), feature extraction and classification are separate sequential operations that may require high-level handcrafted engineering decisions. In contrast, in DL (Alharthi *et al* 2019), feature extraction and classification are integrated and automatically performed (Lih *et al* 2020) (figure 2). A DL model typically comprises some form of artificial neural network (ANN) with many hidden layers that can automatically extract prominent features from high-dimensional raw data (e.g. images) (Lundervold and Lundervold 2019, Joloudari *et al* 2020, Nosratabadi *et al* 2020, Shi *et al* 2020, Huang *et al* 2021).



An example of the DL model is the deep convolutional neural network (DCNN) (Panayides *et al* 2020, Huang *et al* 2021), which may have tens to hundreds of hidden layers (Faust *et al* 2018), including several convolutional, pooling, and fully-connected layers (figure 3). The input signals are convolved by the convolutional kernels to extract features. The pooling layer reduces the network's computational complexity while maintaining a consistent feature map resolution. Two well-known types of pooling layers are max-pooling and average pooling. The last layer of the DCNN is a fully-connected layer that outputs the final classification results. DL models usually yield excellent performance for detecting and classifying early changes in the disease course (Chen *et al* 2017, Ker *et al* 2017, Litjens *et al* 2017, Rawat and Wang 2017, Shen *et al* 2017, Faust *et al* 2018, Esteva *et al* 2019, Ali *et al* 2020, Sun *et al* 2020). A review paper on MI detection published in 2017 (Ansari *et al* 2017) mainly focused on traditional ML methods as many DL papers had not been published then. Our current paper focuses on both ML and DL techniques employed for MI detection using ECG signals.

This paper has systematically reviewed recent studies on artificial intelligence for MI diagnosis, stratified by ML- or DL-based approaches. The rest of the paper is structured as follows: search methodology is presented in section 2; literature review on AI for MI diagnosis in section 3; results and discussion in section 4; future works in section 5; and conclusion in section 6.

2. Search strategy

We performed a search for works published between January 1st, 1992 to January 31st, 2022, on the Google Scholar engine using the keywords 'myocardial infarct diagnosis', 'artificial intelligence', 'machine learning', and 'deep learning'. As a result, we retrieved 64 papers (31 and 33 related to ML and DL, respectively), most of which were published by IEEE, Elsevier, and Springer (figure 4).

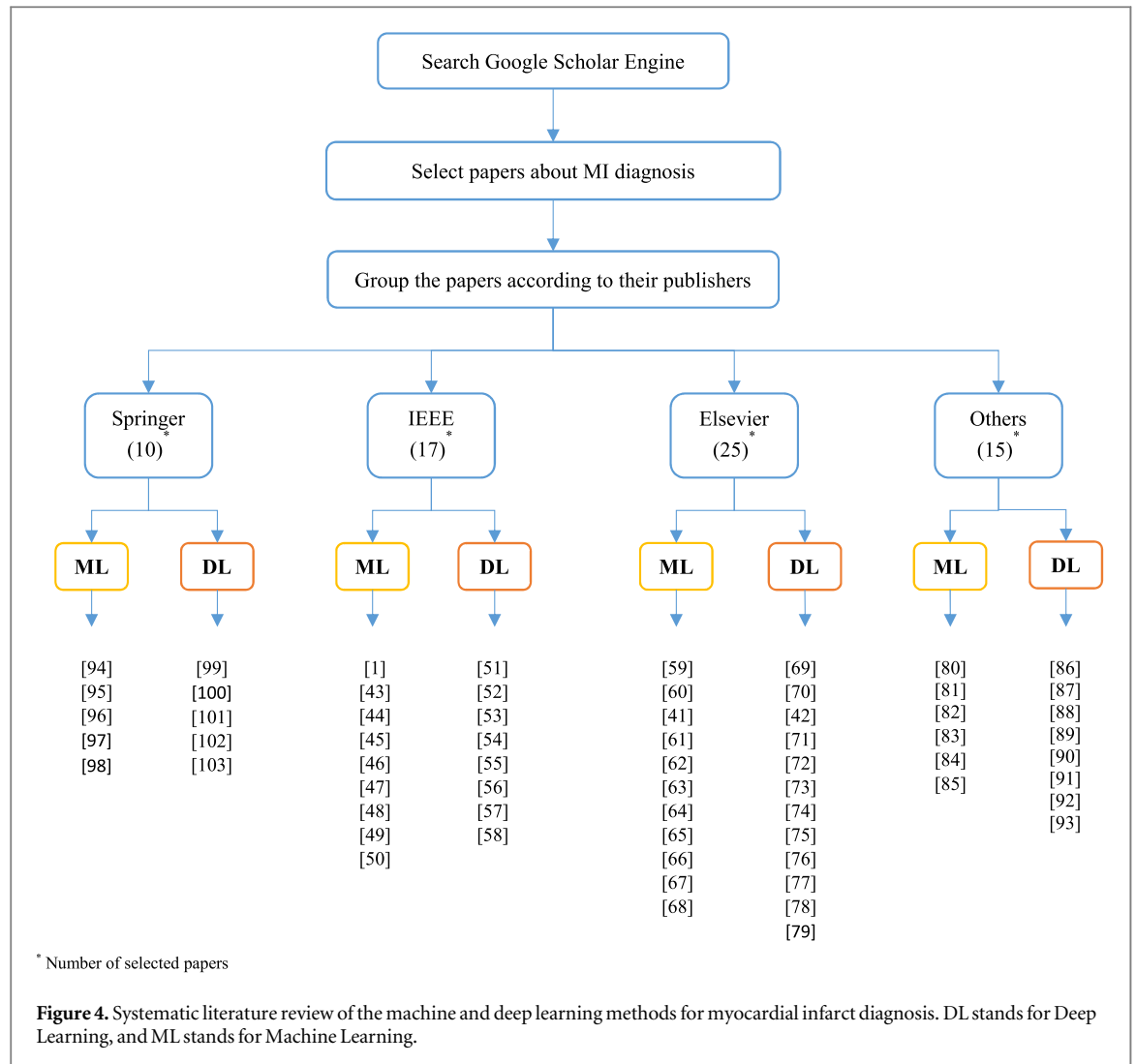
3. A systematic literature review for MI diagnosis

In this section, the databases used in the investigated papers are summarized. The papers are grouped according to the classification algorithms used in each of them.

3.1. Public ECG datasets for MI

ECG is a key noninvasive approach for the diagnosis of cardiovascular diseases, and the research community can benefit from high-quality and publicly available ECG datasets. In the following, some of the most famous public datasets in this field are introduced. Most of the research for MI diagnosis has used these datasets.

One famous ECG dataset is the PTB diagnostic ECG dataset (<https://physionet.org/content/ptbdb/1.0.0/> (accessed 2022), Bousseljot *et al* 1995). Publicly available for over 20 years, it has been used in various studies on MI diagnosis, including several in this review. More recently, Wagner *et al* (Wagner *et al* 2020a) released one of the largest ECG datasets named PTB-XL (<https://physionet.org/content/ptb-xl/1.0.1/> (accessed 2022), Wagner *et al* 2020b). Access to this dataset had previously been limited but was recently made available for public use in 2020. The dataset comprises 21,837 10 s 12-lead ECG records from 18,885 patients (52% male, 48% female; median age 62 years, range 0 to 95 years) with diverse diagnoses. In the PTB-XL, 12-lead ECGs of 148 MI



patients and 52 healthy subjects can be used for training MI diagnosis models. Another publicly available ECG dataset is the MIT-BIH Arrhythmia database (<https://physionet.org/content/mitdb/1.0.0/> (accessed 2022), Moody and Mark 2001), which has been widely used for the classification of cardiac arrhythmia. A short description is given here as it has been used for arrhythmia classification in experiments conducted by some of the reviewed papers. MIT-BIH consists of 48 half-hour excerpts of two-channel ambulatory ECG recordings of 47 subjects acquired between 1975 and 1979 from inpatients (about 60%) and outpatients (about 40%) at the Beth Israel Hospital, Boston. Twenty-three recordings were randomly chosen from 4000 24-hour ambulatory ECG recordings as well as 25 other recordings from patients with less common but clinically significant arrhythmia selected from the same set (Moody and Mark 1990, Acharya *et al* 2016).

3.2. ML-based methods

ML approaches for MI classification include k-nearest neighbor (KNN), decision tree (DT), support vector machine (SVM), naïve Bayes (NB), and random forest (RF), as well as ANN, which is inspired by human neuronal function (Jahmunah *et al* 2021). In the following, we reviewed the papers in this field and grouped them according to the classification algorithms used in these papers.

3.2.1. Artificial neural networks

Hedén *et al* (Hedén *et al* 1997) applied ANN classification to 1,120 MI ECGs and 10,452 normal ECGs and achieved 95.0% sensitivity and 86.3% specificity. Haraldsson *et al* (Haraldsson *et al* 2004) used a Bayesian ANN trained with Hermite expansion coefficients BANN-HE to construct a 12-lead ECG-based MI diagnostic system that showed strong discriminative utility for MI vs. normal (C statistic 83.4%) on 2,238 ECG signals from emergency department attendance. Kora *et al* (2015) used an improved bat algorithm (IBA) to extract the major properties of each pulse from the PTB database, which included 148 MI and 52 normal individuals. A back-propagation Levenberg–Marquardt Neural Network (LMNN) classifier was used to input the best features. The

combination of optimized features, IBA and LMNN achieved 98.9% accuracy for MI diagnosis, outperforming methods like SVM, scalar conjugate gradient neural network, LMNN, and KNN. Zeng *et al* (2020) used 12-lead and Frank XYZ lead ECG signal segments from the PTB database to propose a neural network with RBF for early MI diagnosis. To develop cardiac vectors based on the synthesis of 12-lead ECG signals and Frank XYZ leads, nonlinear feature extraction methods such as tunable quality factor wavelet transformations, variational mode decomposition, and phase space reconstruction were applied. To model, diagnose, and classify MI vs. healthy people, these feature vectors were fed into dynamical estimators incorporating a Radial Basis Function (RBF)-neural network. The method attained the best accuracy of 97.98% using a 10-fold Cross-Validation (CV).

3.2.2. SVM

Sun *et al* (Sun *et al* 2012) described a method for diagnosing MI using 12-lead ECGs called latent topic multiple instance learning (LTMIL). Signal processing was done with discrete cosine transform (DCT) bandpass filters. Fifth-order polynomial fitting was utilized to establish the 74-dimensional feature spaces. A particle swarm optimizer was used for variable weighting. SVM, KNN, RF, and ensemble learning were utilized for classification. KNN ensemble combined with LTMIL achieved the highest accuracy of 90%. For MI diagnosis, Sharma *et al* (Sharma *et al* 2015) used a multiscale energy and eigenspace feature-based technique. After applying wavelet decomposition of multi-lead ECG signals to clinical components in various subgroups, a frame with four beats from each ECG lead was utilized to detect MI. Multilayer ECG frames were used to adjust the properties of the 72-dimensional vectors of 12-lead ECG data. The ECG signals were classified using SVM with RBF kernel, linear SVM, and KNN, which attained 96.0% accuracy for MI diagnosis. Kumar *et al* (2017) used sample entropy in a flexible analytical wavelet transform (FAWT) framework to diagnose MI using ECG data. FAWT was utilized to break down each ECG beat into sub-band signals after the ECG signals were split into beats. These sub-band signals were used to calculate sample entropies, which were then input into several classifiers. The classification accuracy of FAWT combined with least-squares SVM (LS-SVM) was 99.31%, outperforming RF, J48 decision tree, and Back Propagation Neural Network (BPNN) techniques.

Diker *et al* (Diker *et al* 2018) combined SVM with a genetic algorithm (GA) to diagnose MI on ECGs from the PTB database. 23 morphological, time-domain, and Discrete Wavelet Transform (DWT) features were extracted from ECG signals, and their dimensionality was reduced to 9 using GA. The SVM classifier attained 87.8% and 86.44% accuracy rates using the reduced 9 and original 23 features, respectively. Han and Shi (Han and Shi 2019) explored methods such as SVM (with RBF, linear, and polynomial kernels), Bagging Trees (BTs), and BPNN for MI diagnosis and developed a hybrid feature set for ECG signals composed of energy entropy as global features and local morphological features. The global features were computed using maximal overlap discrete wavelet packet transform (MODWP) of ECG signals. After the fusion of multi-lead ECG signals, Principal Component Analysis (PCA), linear discriminant analysis, and Locality Preserving Projection (LPP) approaches were employed to reduce the number of features. SVM-RBF with 10-fold CV achieved the greatest accuracy of 99.81% utilizing the 18 features for the intra-patient pattern in trials using ECGs from the PTB database. Valizadeh *et al* (Valizadeh *et al* 2021) proposed a novel parametric-based feature selection based on the left ventricle's 3D spherical harmonic shape descriptors to distinguish MI patients from healthy ones. The method was based on the hypothesis that spherical harmonic coefficients of the parameterized endocardial shapes would be different for MI patients and healthy subjects. The method was started by preprocessing cine-MRI images from the automated cardiac diagnosis challenge dataset. Next, parametric-based features, i.e. spherical harmonic coefficients, were extracted and normalized. PCA was applied to the normalized features, and the results were used to train multiple classifiers, among which SVM attained the best performance.

3.2.3. KNN

Arif *et al* (Arif *et al* 2012) diagnosed MI using the KNN method on 20,160 ECG beats obtained from the PTB database. The experimental phase used 10,080 and 711 heartbeats for non-pruning and pruning training, respectively. A dual wavelet transform was applied to the ECG signals to determine the 36 components of the feature vector. Finally, MI cases were divided into 11 classes (10 classes for the various infarct sites and one class for normal subjects). They attained 98.8% overall classification accuracy and sensitivity and specificity exceeding 90% for MI localization. Further, a sensitivity of 99.97% and specificity of 99.9% was obtained for MI detection. In the PTB database, Acharya *et al* (Acharya *et al* 2016) used a KNN classifier to differentiate MI vs. normal ECGs in the PTB database. Each signal underwent four levels of DWT decomposition using Daubechies' six wavelet basis function, and 12 types of nonlinear properties were extracted from the DWT coefficients. The discriminative features ranked based on their t-values, F-values, and analysis of variance (ANOVA) were used to derive the rankings of the normal class and ten types of MI. The method achieved 98.80% classification accuracy for MI vs. normal classes based on 47 characteristics obtained from Lead V5. Moreover, 98.74% accuracy for 11-class classification based on 25 characteristics from Lead V3 and 99.97% accuracy for MI localization based on Lead V3 was achieved. In another study, Acharya *et al* (Acharya *et al* 2017a) compared DWT, empirical mode

decomposition (EMD), and DCT methods for coronary artery disease and MI diagnoses. ECG signals underwent DCT, DWT, and EMD to obtain the corresponding coefficients, which were then reduced using the LPP method. The LPP features were ranked using their F-values, and highly ranked coefficients were then fed to the KNN classifier. DCT coefficients paired with KNN yielded the maximum accuracy of 98.5%. Lin *et al* (Lin *et al* 2020) decomposed ECG signals using MODWP and extracted features such as variance, interquartile range, Pearson correlation coefficient, Hoeffding's D correlation coefficient, and Shannon entropy of the wavelet coefficients. Inputting these features to a KNN classifier, they attained 99.57% accuracy for MI diagnosis using ECGs in the PTB database.

3.2.4. Decision trees

Zhang *et al* (Zhang *et al* 2019a) proposed stacked sparse autoencoder (SAE) with a treebagger (TB) for diagnosing MI using single-lead ECG signals of the PTB database. SAE employs a layer-wise training technique to avoid the vanishing gradient problem in the feature extraction network. Without an input tag, it may learn the best feature expression from the heartbeat. As a result, this method can extract unique characteristics from single-lead ECG signals. By merging the findings of numerous decision trees and feature improvements, the TB classifier was created to best simulate MI diagnosis. The model attained accuracy, sensitivity, and specificity of 99.90%, 99.98%, and 99.52%, respectively. Kayikcioglu *et al* (Kayikcioglu *et al* 2020) deployed ensemble classification algorithms such as boosted trees, BTs, and subspace KNN in addition to standard SVM and KNN algorithms for MI diagnosis using ECGs from the MIT-BIH Arrhythmia, European ST-T, and the Long-Term ST databases. The datasets were classified into four classes: healthy, arrhythmia, ST depression, and ST elevation (ST changes can be present in MI). Quadratic time-frequency distributions including smoothed Wigner-Ville, the Choi-Williams, the Bessel and the Born-Jordan were applied on 5-lead ECG signals for feature extraction. The best accuracy of 94.23% was obtained for the weighted KNN algorithm using features extracted by the Choi-Williams time distribution.

3.2.5. Deep learning

DL can learn from huge datasets due to their complex structure with several layers. Therefore, DL models such as DCNN, long short-term memory (LSTM), recurrent neural network (RNN), and autoencoder network can be used for disease classification and generally outperform ML methods in terms of signal processing and classification (Sharifrazi *et al* 2020).

Reasat and Shahnaz (Reasat and Shahnaz 2017) designed a DCNN to identify inferior MI ECG signals from healthy ones using ECG Leads II, III, and AFV inputs. They tested their network on data from one patient and trained it on data from the rest of the patients. The model attained 84.54% accuracy, outperforming stationary wavelet transform (SWT) with KNN and SWT with SVM (Sharma and Sunkaria 2018). Gupta *et al* (Gupta *et al* 2020) observed that data from ECG Leads V6, V3, and II were critical for identifying MI correctly and applied this insight to modify the ConvNetQuake neural network for MI classification. The modified model achieved 99.43% accuracy for MI diagnosis using only 10 s of raw ECG recordings as input. Tripathy *et al* (Tripathy *et al* 2019) presented a novel MI diagnostic approach that combined deep layer LS-SVM with features obtained by time-scale decomposition of 12-lead ECG signals using Fourier–Bessel series expansion-based empirical wavelet transform. The system achieved 99.97% accuracy. Zhang *et al* (Zhang *et al* 2019b) used Gramian angular difference field (GADF), PCA network (a lightweight DCNN-like model), and linear SVM in combination to extract salient features of Lead II ECGs from the PTB database. For ECG-level classification, the model achieved 98.44% (beat type: no noise) accuracy rates with a 5-fold CV. At the subject level, 93.17% accuracy was achieved. Feng *et al* (Feng *et al* 2019) proposed a multichannel classification algorithm that combined a 16-layer DCNN with LSTM for MI diagnosis. ECG signals were preprocessed to extract heartbeat segments, and the extracted segments were then fed to the DCNN to obtain the feature map. Final classification results were output by LSTM based on the received feature map. The system attained 95.4% accuracy without the use of handcrafted features. Liu *et al* (Liu *et al* 2019) combined DCNN and RNN to build a hybrid network named multiple-feature-branch convolutional bidirectional RNN (MFB-CBRNN) for MI diagnosis using 12-lead ECG signals. The bidirectional long short term memory (BLSTM) network was used to summarize the features from the 12-lead ECG records. The model attained 99.90% and 93.08% accuracy rates at the ECG and subject levels, respectively.

Han and Shi (Han and Shi 2020) used 12-lead ECG signals from the PTB database to create a multi-lead residual neural network (ML-ResNet) model with three residual blocks and feature fusion for MI diagnosis. The model attained 95.49% and 99.92% accuracy rates for the inter- and intra-patient schemes, respectively. Fu *et al* (Fu *et al* 2020) developed a multi-lead attention mechanism (MLA-CNN-BiGRU) framework for diagnosing MI using 12-lead ECG signals from the PTB database. The model performance was enhanced by weighting the different leads in proportion to their contributions. In addition, interrelated characteristics between leads were exploited to extract discriminative spatial features using the two-dimensional DCNN module. With the memory capability of BiGRU, the model was able to exploit the temporal features of ECG signals, and a combination of

temporal and spatial features was used for classification. The model achieved 99.93% and 96.5% accuracy rates for intra- and inter-patient schemes, respectively.

Jahmunah *et al* (Jahmunah *et al* 2021) compared the performance of DCNN vs. Gabor-filter DCNN models for classifying subjects into MI, coronary artery disease, congestive heart failure, and normal classes. In the latter, eight convolutional layers of the DCNN were replaced with Gabor filters, which reduced the computational complexity. Based on Lead II ECG signals, the Gabor-filter DCNN and DCNN models attained average accuracy rates of 99.55% and 98.74%, respectively, for the four-class classification task. Kim *et al* (Kim *et al* 2020) utilized U-Net architecture combined with the Monte Carlo dropout technique to estimate the uncertainty of the U-Net model using cardiac perfusion images for myocardial segmentation. Their approach obtained a better Dice similarity of 0.806 ± 0.096 (average \pm standard deviation) compared to rival methods such as semi-automatic U-Net (0.808 ± 0.084) and automatic U-Net (0.729 ± 0.147).

Garland *et al* (Garland *et al* 2021) studied the possibility of using CNNs to distinguish MI subjects from healthy ones. To this end, the classification performance of four different CNNs (commonly used in surgical/anatomical histopathology) was investigated on a dataset with 150 images (50 normal myocardium, 50 acute MI, and 50 old MI). The authors reported that InceptionResNet v2, with 100% accuracy, was a promising candidate for MI diagnosis. As another MI diagnosis study based on non-ECG data, Degerli *et al* (Degerli *et al* 2021) gathered an echocardiographic dataset (HMC-QU) for MI detection, which was publicly available. They proposed a three-phase approach to early MI detection. The first phase involved using DL to segment the left ventricle. Next, the segmented region was analyzed for feature engineering. Finally, in the third phase, MI detection was performed. As mentioned before, precise and timely MI identification is critical for patients' survival. Myocardial contrast echocardiography (MCE) has been used in MI diagnosis but is time-consuming, subjective, and highly operator-dependent. In (Guo *et al* 2021), a new DL network named polar residual network (PResNet), based on ResNet, was proposed for automated computer-aided MI diagnosis based on MCE images. The authors defined a new polar layer in the structure of PResNet that mapped subsections of MCE to the polar map. The rest of the convolutional and residual layers of the networks were used to extract salient features from the polar layer.

4. Results and discussion

The results of the ML-based and DL-based methods are summarized in tables 1 and 2. From table 1, among ML models, SAE + TB proposed by Zhang *et al* (Zhang *et al* 2019a) attained the best accuracy of 99.90% using the PTB database. From table 2, the DCNN method has the highest accuracy of 99.95% for MI diagnosis using the PTB database.

More ML works were published previously, but DL publications are gradually superseding the numbers in recent years. In 2021, there were 17 DL vs. 4 ML publications on MI diagnosis. The secular trend of ML and DL publications is shown in figure 5. Hence, the number of papers on MI diagnosis using DL-based methods has increased recently. Even though DL-based MI detection began later than ML-based detection, the number of DL publications has caught up with ML publications; 33 papers for DL and 31 papers for ML (figure 6(a)). However, the model performance of ML publications is more consistent than that of DL publications. The box-and-whiskers plot in figure 6(b) shows that the model performance of ML-based MI detection has a lower standard deviation, and the range of accuracy scores falls between 79.0 to 99.9%, while the range of accuracy score for DL-based MI detection is 66.8 to 99.95%.

Despite many studies proposing various ML/DL approaches for medical applications, ML/DL still suffers from some limitations. First of all, medical datasets may contain samples with missing values. These samples are not readily usable during ML/DL model training. Avoiding samples with missing values causes biased (Wallert *et al* 2017) training/evaluation of models, which is not desirable. DL methods have huge potential for knowledge learning and representation, but only if a sufficient number of training samples are fed. In the medical domain, gathering and labeling a large number of samples is usually challenging (Than *et al* 2019). On the other hand, a limited number of training samples causes DL models to underperform in the test phase. Furthermore, DL models are not error-free, and wrong predictions can be catastrophic in medical applications. Therefore, ML/DL models must be able to determine whether their outputs are trustworthy or not. Unfortunately, not all models are equipped with such ability. The ML/DL community has come a long way. However, current ML/DL methods are still not robust enough to fully gain medical experts' trust. Therefore, ML/DL application in the medical domain is still limited.

5. Future work

Due to the rapid growth of using AI algorithms in all branches of science, including medicine, a bright future can be imagined for using these algorithms in diagnosing myocardial infarction. Furthermore, among AI algorithms, the outstanding representation power of DL has led to the rapid growth of DL-based studies for MI detection. However, DL-based approaches demand high computational power and massive memory that may

Table 1. Summary of machine learning-based publications on MI diagnosis.

No.	Author, Year	Methods	End-to-End	No. K-fold CV	Dataset (No. of leads, Subjects)	Division Solutions	Performance ^a
1	(Reddy <i>et al</i> 1992)	ANN	Yes	NC	Leads: V2-V4 Subjects: 272 MI, 479 Normal	inter-beat	ACC:79.00 Spe: 97.00
2	(Hedén <i>et al</i> 1997)	ANN	Yes	8-fold CV	Leads: 12 leads Subjects: 1120 MI, 10452 Normal from PTB database	inter-beat	Spe: 86.30 Sen: 65.90
3	(Lu <i>et al</i> 2000)	Neuro-fuzzy classifier	No	NC	Leads: 12 leads, Subjects: 20 normal, 104 MI	inter-beat	ACC: 89.40 Spe: 90.00 Sen: 84.60
4	(Haraldsson <i>et al</i> 2004)	ANN	Yes	3-fold CV	Leads: 12 leads Subjects: 2238 ECGs, 699 men and 420 women for MI group, 578 men and 541 women for Normal group	inter-beat	ACC: 94 AUC: 83.40
5	(Zheng <i>et al</i> 2006)	SVM	No	10-fold CV	Leads: 192-lead body surface potential maps Subjects: 57 MI, 59 Normal from PTB database	inter-beat	ACC: 82.80 Pre: 86.30 Spe: 88.10 Sen: 77.20
6	(Arif <i>et al</i> 2010)	BPNN + PCA	No	NC	Leads: 12 leads Subject: 148 MI and 52 Normal from PTB database	inter-beat	ACC: 93.70 Spe: 99.10 Sen: 97.50
7	(Sun <i>et al</i> 2012)	LTMIL + SVM	No	10-fold CV	Leads: 12 leads Subject: 369 MI, 79 Normal from PTB database	inter-beat	ACC: 90.00 Spe: 82.40 Sen: 92.60
8	(Arif <i>et al</i> 2012)	KNN	No	10-fold CV	Leads: 12 leads Subjects: 10 types of MI and 1 healthy from PTB database	inter-beat	ACC: 98.30 Spe: 99.90 Sen: 99.97
9	(Chang <i>et al</i> 2012)	HMMs + GMMs	No	NC	Leads: Leads V1-V4 Subjects: 1129 samples of heartbeats; 582 MI, 547 Normal	inter-beat	ACC: 85.71 Spe: 79.82 Sen: 85.71
10	(Safdarian <i>et al</i> 2014)	NB	No	NC	Leads: Lead II Subjects: 290 subjects and 549 records from PTB database	inter-beat	ACC: 94.74
11		IBA + LMNN	No	NC	Leads: Lead III	inter-beat	ACC: 98.90

Table 1. (Continued.)

No.	Author, Year	Methods	End-to-End	No. K-fold CV	Dataset (No. of leads, Subjects)	Division Solutions	Performance ^a
12	(Kora and Kalva 2015) (Sharma <i>et al</i> 2015)	SVM-RBF	No	5-fold CV	Subjects: 52 Normal 148 MI from PTB database Leads: 12 leads	inter-beat	Spe: 92.20 Sen: 93.34 ACC: 96.00
13	(Acharya <i>et al</i> 2016)	DWT coefficients+KNN	No	10-fold CV	Subjects: 148 MI, 52 Normal from PTB database Leads: Lead V5	inter-beat	Spe: 99.00 Sen: 93.00 ACC: 98.80
14	(Acharya <i>et al</i> 2017a)	DCT coefficients+KNN	No	10-fold CV	Subjects: 52 normal, 148 MI from PTB database Leads: Lead II	inter-beat	Spe: 96.27 Sen: 99.45 ACC: 98.50
15	(Kumar <i>et al</i> 2017)	LS-SVM-RBF	No	10-fold CV	Subjects: 148 MI, 52 Normal from PTB database Leads: Lead II	inter-beat	Spe: 98.50 Sen: 99.70 ACC: 99.31
16	(Khatun and Morshed 2017)	BTs	No	10-fold CV	Subjects: 52 Normal and 148 MI from PTB database Leads: 12 leads	inter-beat	Spe: 98.12 Sen: 99.62 ACC: 99.7
17	(Acharya <i>et al</i> 2017a)	CWT-based controlet+KNN	No	10-fold CV	Subjects: 79 normal, 346 MI from PTB database Leads: 12 leads	inter-beat	Pre: 99.32 Spe: 100.00 Sen: 99.41 F1: 99.36 ACC: 99.55
18	(Dohare <i>et al</i> 2018)	SVM + PCA	No	10-fold CV	Subjects: 148 MI, 52 Normal from PTB database Leads: 12 leads	inter-beat	Spe: 99.24 Sen: 99.93 ACC: 98.33
19	(Diker <i>et al</i> 2018)	GA + SVM	No	10-fold CV	Subjects: 60 MI, 60 Normal from PTB database 549 records from 290 subjects Leads: 12 leads	inter-beat	Spe: 100.00 Sen: 96.66 ACC: 87.80

Table 1. (Continued.)

No.	Author, Year	Methods	End-to-End	No. K-fold CV	Dataset (No. of leads, Subjects)	Division Solutions	Performance ^a
20	(Sharma and Sunkaria 2018)	SWT + SVM	No	10-fold CV	Subjects: 148 MI, 52 Normal from PTB database Leads: Lead-II, III and aVF	inter-beat	Spe: 88.67 Sen: 86.97 ACC: 98.84
21	(Han and Shi 2019)	SVM-RBF, BPNN, Bagging	No	10-fold CV	Subjects: 148 MI, 52 Normal from PTB database Leads: 12 leads	inter-patient	Pre: 98.41 Spe: 98.29 Sen: 99.35 ACC: 99.75
22	(Zhang <i>et al</i> 2019a)	SAE + TB	Yes	10-fold CV	Subjects: 148 MI, 52 Normal from PTB database Leads: Lead II	inter-patient	Pre: 99.70 Spe: 99.37 Sen: 99.37 F1: 99.54 ACC: 99.90
23	(Zeng <i>et al</i> 2020)	RBF- neural network	No	10-fold CV	Subjects: 148 MI, 52 Normal from PTB database Leads: 15 leads	inter-beat	Pre: 99.52 Sen: 99.98 ACC: 97.98 Pre: 99.45 Spe: 97.44 Sen: 98.09
24	(Kayikcioglu <i>et al</i> 2020)	Weighted KNN	No	10-fold CV	Leads: Leads V1-V5 Subjects: European ST-T (70 ECG recordings), MIT-BIH Arrhythmia database (46 different patients) and Long-Term ST (70 ECG recordings)	inter-beat	ACC: 94.23 Spe: 98.15 Sen: 95.72
25	(Liu <i>et al</i> 2020)	Dual-Q TQWT + DWPT + MPCA + TB	No	10-fold CV	Leads: 12 leads and 3 Frank leads (VX, VY, VZ) Subjects: 78 Normal, 328 MI from PTB database	inter-beat	F1: 95.30 ACC: 97.46 Spe: 90.26 Sen: 99.09
26	(Lin <i>et al</i> 2020)	KNN	No	10-fold CV	Leads: 12 Leads Subjects: 148 MI and 52 Normal from PTB database	inter-beat	ACC: 99.57 Spe: 98.79 Sen: 99.82
27			No		40 cine-MRI	inter-beat	ACC: 97.5

Table 1. (Continued.)

No.	Author, Year	Methods	End-to-End	No. K-fold CV	Dataset (No. of leads, Subjects)	Division Solutions	Performance ^a
	(Valizadeh <i>et al</i> 2021)	Parametric-based technique + spherical harmonic-based feature selection + PCA SVM/KNN/RF		leave-one-out cross-validation scheme	Subjects: 20 Normal and 20 MI from the automated cardiac diagnosis challenge database		Spe: 98.79
28	(Shahnawaz and Dawood 2021)	ANN	Yes	10-fold CV	Leads: single lead Subjects: 148 MI, 52 Normal from PTB database	inter-beat	Sen: 99.82 ACC: 99.10
29	(Panchavati <i>et al</i> 2021)	Gradient boosted tree model	No	3-fold CV	Subjects: 253 MI, 1600 Normal, Electronic health records (age, glucose, systolic/diastolic blood pressure, etc)	inter-beat	Spe: 98.10 Sen: 100.00 F1: 99.00 Spe: 70.00
30	(Sulthana and Jaithunbi 2022)	Probabilistic PCA + multi-linear regression + RBF based SVMs	No	5-fold CV	517 tuples with 20 attributes,	inter-beat	Sen: 87.00 AUC: 87.00 ACC: 94.03
31	(Mohammad <i>et al</i> 2022)	ANN	Yes	NC	Clinical tests Subjects: 139288 MI in the SWEDEHEART registry and 30971 MI in the Western Denmark Heart Registry Clinical data (age, sex, medical history, etc)	inter-beat	Pre: 26.00 Spe: 76.60 Sen: 80.20 AUC: 85.00

^a The performance metrics across studies are not directly comparable due to differences in ECG acquisition (e.g. number of leads), subjects and methodology. ACC: Accuracy, Sen: Sensitivity, Spe: Specificity, Pre: Precision, AUC: Area under the Curve, F1:F1-score, NC: not considered.

Table 2. Summary of deep learning-based publications on MI diagnosis.

No.	Author, Year	Methods	End-to-End	No. K-fold CV	Dataset (No. of leads, Subjects)	Division Solution	Performance ^a
1	(Acharya <i>et al</i> 2017b)	DCNN	Yes	10-fold CV	Leads: Lead II Subjects: 148 MI, 52 Normal from PTB database	inter-beat	ACC: 95.22 Spe: 94.19 Sen: 95.49
2	(Reasat and Shahnaz 2017)	DCNN	Yes	NC	Leads: Leads II, III and AVF Subjects: 148 MI, 52 Normal from PTB database	inter-beat	ACC: 84.54 Spe: 84.09 Sen: 85.33
3	(Lui and Chow 2018)	DCNN-LSTM	Yes	10-fold CV	Leads: Lead I Subjects: 148 MI and 52 Normal from PTB database	inter-beat	Pre: 97.20 Spe: 97.70 Sen: 92.40 F1: 94.60
4	(Baloglu <i>et al</i> 2019)	DCNN	Yes	kNC	Leads: lead V4 Subjects: 52 Normal, 148 MI from PTB database	inter-beat	ACC: 99.78 Pre: 99.83 Spe: 99.97 Sen: 99.8 F1: 99.80
5	(Tripathy <i>et al</i> 2019)	DL-LSSVM	No	5-fold CV	Leads: 12 leads Subjects: 148 MI, 52 Normal from PTB database	inter-beat	ACC: 99.97 Spe: 99.95 Sen: 100.00
6	(Zhang <i>et al</i> 2019b)	GADF + PCANet + Linear SVM	No	5-fold CV	Leads: Lead II Subjects: 52 Normal, 148 MI from PTB database	inter-patient	ACC: 99.49 Pre: 99.61 Spec: 98.08 Sen: 99.78
7	(Feng <i>et al</i> 2019)	DCNN + LSTM	Yes	10-fold CV	Leads: Lead I Subjects: 148 MI, 52 Normal from PTB database	inter-beat	ACC: 95.40 Spe: 86.50 Sens: 98.20 F1: 96.8
8	(Liu <i>et al</i> 2019)	MFB-CBRNN + BLSTM	Yes	5-fold CV	Leads: 12 leads Subjects: 148 MI, 52 Normal from PTB database	inter-patient	ACC: 99.90 Pre: 99.91

Table 2. (Continued.)

No.	Author, Year	Methods	End-to-End	No. K-fold CV	Dataset (No. of leads, Subjects)	Division Solution	Performance ^a
9	(Strodthoff and Strodthoff 2019)	DCNN-FC	Yes	10-fold CV	Leads: 12 leads Subjects: 127 MI, 52 Normal	inter-beat	Spe: 99.54 Sen: 99.97 Spe: 89.7
10	(Gupta et al 2020)	DCNNQuak	Yes	100-fold CV	Leads: 12 leads along with 3 Frank leads	inter-beat	Sen: 93.3 ACC: 94.67
11	(Han and Shi 2020)	ML-ResNet	Yes	5-fold CV	Subjects: 52 Normal, 148 MI from PTB database Leads: 12 leads Subjects: 52 Normal, 113 MI from PTB database	inter-patient	ACC: 95.49 Spe: 97.37 Sen: 94.85 F1: 96.92 AUC: 98.00 Dice score: 80.60
12	(Kim et al 2020)	Automatic U-Net + Monte Carlo dropout	Yes	NC	Leads: NC Subjects: 14 coronary artery disease, 8 hypertrophic cardiomyopathy, and 13 Normal	inter-beat	ACC: 92.72
13	(Natesan and Gothai 2020)	DCNN + DA	Yes	NC	Leads: 12 leads Subjects: 148 MI, 52 Normal from PTB database	inter-patient	ACC: 96.50
14	(Fu et al 2020)	MLA-DCNN-BiGRU	Yes	5-fold CV	Leads: 12 leads Subjects: 148 MI, 52 Normal from PTB database	inter-beat	Spe: 93.34 Sen: 97.10 ACC: 73.20
15	(Tadesse et al 2021a)	Transfer learning + Longitudinal	Yes	10-fold CV	Leads: 12 leads Subjects: 148 MI, 52 Normal from PTB database; 11853 MI, 5528 Normal from GCI database	inter-beat	Pre: 83.90 Spe: 68.60 Sen: 75.30 F1: 79.40 AUC: 79.8 ACC: 99.95
16	(Jahmunah et al 2021)	DCNN	Yes	10-fold CV	Leads: Lead II Subjects: 148 MI, 92 Normal from PTB database	inter-beat	Pre: 99.58

Table 2. (Continued.)

No.	Author, Year	Methods	End-to-End	No. K-fold CV	Dataset (No. of leads, Subjects)	Division Solution	Performance ^a
17	(Garland <i>et al</i> 2021)	InceptionResNet v2	Yes	5-fold CV	150 images: 50 Normal, 50 Acute MI, and 50 Old MI, Histology slides	inter-beat	Spe: 99.95 Sen: 99.95 ACC: 100.00 F1: 100.00
18	(Tadesse <i>et al</i> 2021b)	GoogLeNet (Inception - v3) + Spectral-longitudinal model	Yes	5-fold CV	Leads: 12 leads Subjects: 148 MI, 52 Normal from PTB database; 11853 MI, 5528 Normal from GCI database	inter-beat	For GCI database: Pre: 90.00 Spe: 83.00 Sen: 68.00 AUC: 85.00 For PTB database: Pre: 98.00 Spe: 95.00 Sen: 66.00 AUC: 94.00 ACC: 95.76
19	(Jian <i>et al</i> 2021)	DCNNs-based multi-lead features-concatenate narrow network	No	5-fold CV	Leads: 12 leads Subjects: 148 MI, 52 Normal from PTB database; 11853 MI, 5528 Normal from GCI database	inter-patient	
20	(Wang <i>et al</i> 2021)	Multitask attention learning model	Yes	NC	2414 hand images from 301 patients (182 males and 119 females),	inter-beat	ACC: 82.06 Spe: 83.39 Sen: 80.20 F1: 83.86 AUC: 81.27
21	(Rai and Chatterjee 2021)	DCNN-LSTM + ensemble technique	Yes	NC	Leads: Lead II: 52 Normal, 148 MI from PTB database; 47 subjects from MIT-BIH arrhythmia database	inter-beat	ACC: 99.89 Pre: 99.05 Spe: 99.91 Sen: 99.62 F1: 99.34

Table 2. (Continued.)

No.	Author, Year	Methods	End-to-End	No. K-fold CV	Dataset (No. of leads, Subjects)	Division Solution	Performance ^a
22	(Hammad <i>et al</i> 2021b)	DCNN method based on focal loss	Yes	5-fold CV	Leads: 12 leads Subjects: 147 MI, 53 Normal from PTB database	inter-patient	ACC: 98.84 Spe: 98.31 Sen: 97.63 F1: 97.92
23	(He <i>et al</i> 2021)	DCNN + active learning	Yes	5-fold CV	Leads: 12 leads Subjects: 113 MI, 52 Normal from PTB database, Subjects: 2784 MI, 1967 Normal from PTB-XL database	inter-patient	ACC: 96.99 Pre: 96.87 Sen: 99.40 Sen: 96.86 F1: 96.87
24	(Yadav <i>et al</i> 2021)	DCNN	Yes	NC	Leads: 3 Frank leads, Subjects: 66 MI, 80 normal, and 148 records from PTB database	inter-beat	ACC: 99.82 Spe: 99.65 Sen: 100.00 AUC: 100.00
25	(Degerli <i>et al</i> 2021)	Deep encoder-decoder CNN + SVM	No	5-fold CV	Images: 2349 images Subjects: 72 MI and 37 non-MI, Echocardiography	inter-beat	ACC: 80.24 Pre: 86.85 Spe: 74.03 Sen: 83.09 F1: 84.83
26	(Rai <i>et al</i> 2021)	DCNN + LSTM	No	NC	Leads: Lead II Subjects: 52 Normal, 148 MI from PTB database	inter-beat	ACC: 99.80 Pre: 99.80 Spe: 99.80 Sen: 99.80 F1: 99.80
27	(Wang <i>et al</i> 2021)	DCNN-based residual network	Yes	NC	Leads: 12 leads 18,885 patients from PTB-XL database; 10,646 patients from Chapman University and Shaoxing People's Hospital (Zheng <i>et al</i> 2020)	inter-beat	Pre: 83.00 Spe: 95.10 Sen: 95.10 F1: 88.60 AUC: 97.70

Table 2. (Continued.)

No.	Author, Year	Methods	End-to-End	No. K-fold CV	Dataset (No. of leads, Subjects)	Division Solution	Performance ^a
28	(Guo <i>et al</i> 2021)	Polar residual network	No	NC	Balanced dataset: 2,370 infarct, 2,370 normal; Unbalanced dataset: 2,370 infarct, 13,056 normal; Myocardial contrast echocardiography (MCE)	inter-beat	ACC: 98.90 Pre: 99.60 Spe: 99.60 Sen: 99.60 F1: 99.60 AUC: 99.90 ACC: 99.87
29	(Xiong <i>et al</i> 2021)	Densely connected DCNN-based multi-lead localization method	Yes	10-fold CV	Leads: 12 leads Subjects: 52 Normal, 148 MI from PTB database	inter-beat	Spe: 99.98 Sen: 99.84 ACC: 96.65
30	(Cao <i>et al</i> 2021)	DCNN-based multichannel lightweight model	Yes	10-fold CV	Leads: Leads V2, V3, V5, aVL Subjects: 147 MI, 53 Normal from PTB database	inter-patient	Spe: 97.72 Sen: 94.30 AUC: 96.71 NC
31	(Borisov <i>et al</i> 2021)	Linear SVM + PCA	No	NC	Leads: 12 leads 30 MI, 42 normal	inter-beat	NC
32	(Chen <i>et al</i> 2022)	Framework A (Baseline CNN) + Framework B (Context Encoder Network)	No	NC	Images: 904 Delayed Enhancement cardiac MRI slices	inter-beat	Dice score: 66.80 Jaccard index: 52.4
33	(Liu <i>et al</i> 2022)	Evolving Multi-branch Network	No	5-fold CV	Leads: 12-leads Subjects: 148 MI, 52 Normal from PTB database; 21,837 records from the PTB-XL database	inter-patient	Based on PTB database: ACC: 97.11 Pre: 98.01 Spe: 90.20 Sen: 98.53 F1: 98.30 Based on PTB-XL database: ACC: 90.80 Pre: 94.73 Spe: 85.88 Sen: 92.59

Table 2. (Continued.)

No.	Author, Year	Methods	End-to-End	No. K-fold CV	Dataset (No. of leads, Subjects)	Division Solution	Performance ^a
34	(Wang <i>et al</i> 2022)	Integrating deep auto-weighted supervision and pixel-wise attention network	Yes	NC	subjects: Multi-sequence cardiac MRI, including bSSFP, LGE, T2, from 45 patients	inter-beat	F1: 93.60 Dice score: 72.00 Jaccard coefficient: 57.70 Hausdorff Distance: 14.12
35	(Wang <i>et al</i> 2022)	GAN + DCNN	Yes	5-fold CV	Leads: Lead I Subjects: 52 Normal, 148 MI from PTB database	inter-beat	Acc: 99.06 Pre: 99.14 Spe: 98.65 Sen: 99.33 F1: 99.24 G-Mean: 98.99

^a The performance metrics across studies are not directly comparable due to differences in ECG acquisition (e.g. number of leads), subjects and methodology. ACC: Accuracy, Sen: Sensitivity, Spe: Specificity, Ppv: Positive Predictive Value, Pre: Precision, AUC: Area under the Curve, F1:F1-score, G-Mean: Geometric Mean, NC: not considered.

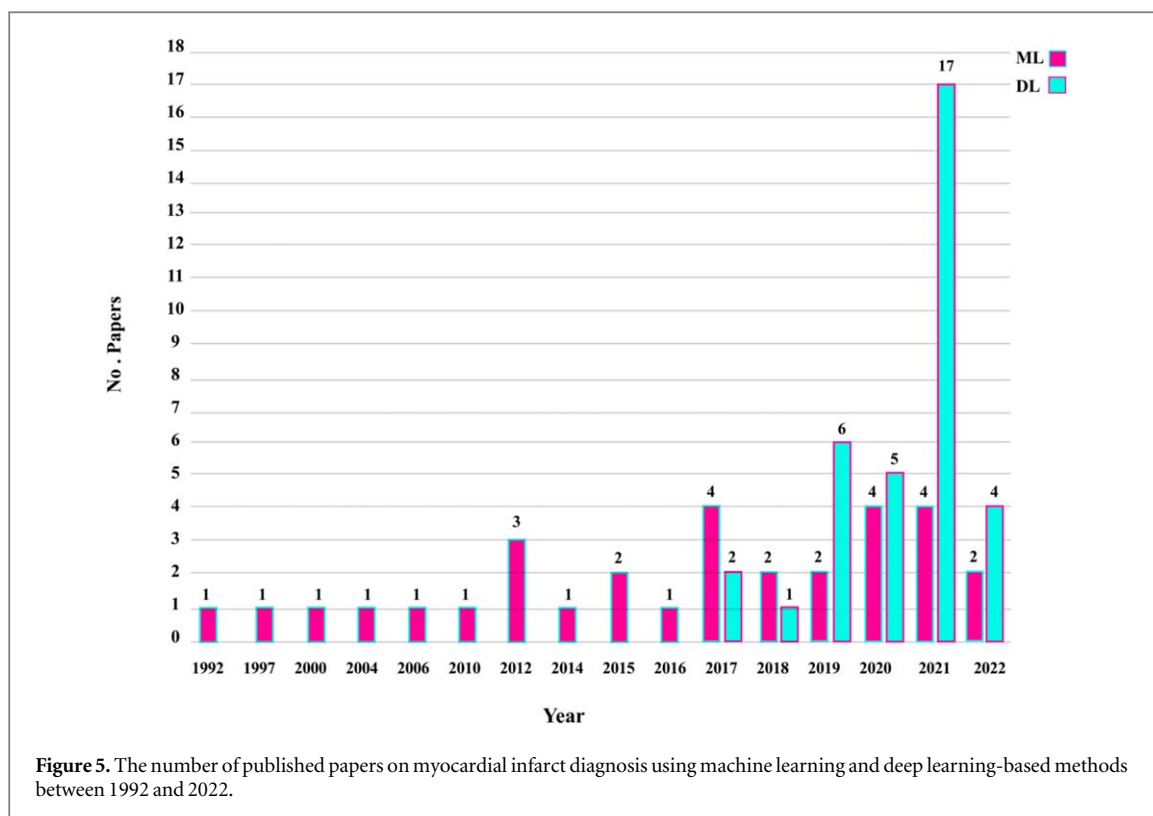


Figure 5. The number of published papers on myocardial infarct diagnosis using machine learning and deep learning-based methods between 1992 and 2022.

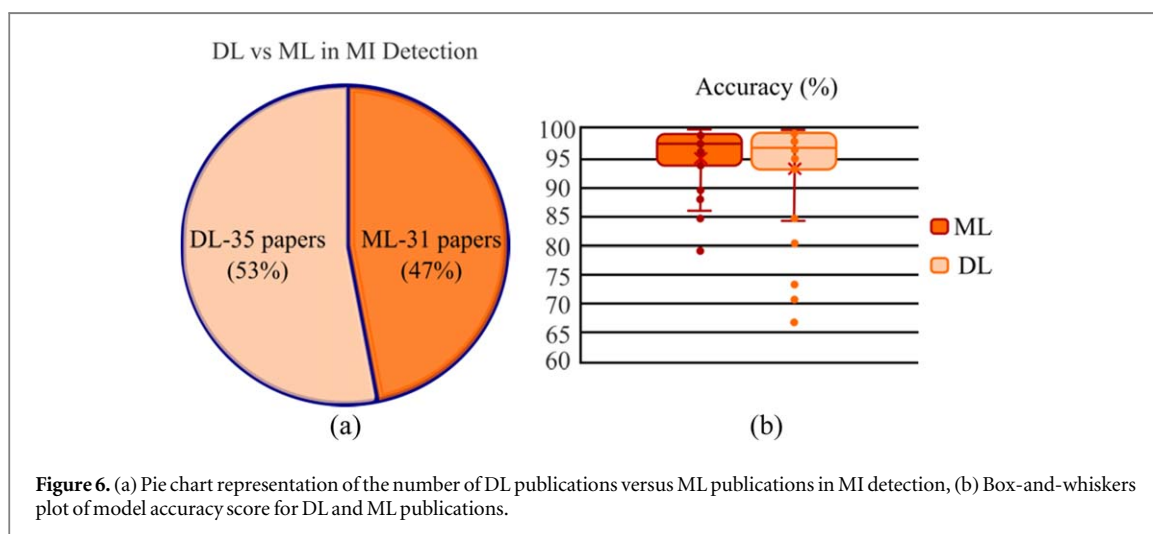
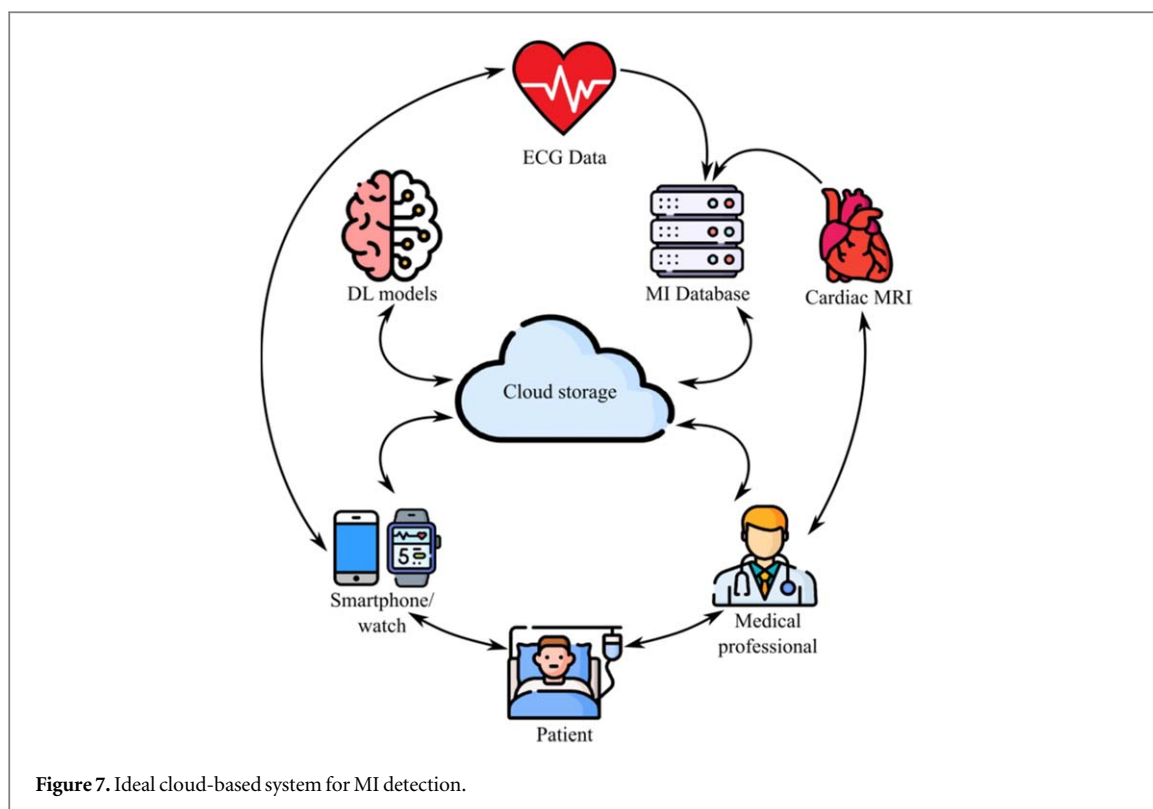


Figure 6. (a) Pie chart representation of the number of DL publications versus ML publications in MI detection, (b) Box-and-whiskers plot of model accuracy score for DL and ML publications.

not be available in all medical centers. Therefore, striving to make DL methods cloud-compatible is a stepping stone toward the wide application of DL in a clinical setting. Currently, the limitation of DL is its massive memory consumption, which makes cloud storage impractical (Tobore *et al* 2019). Hence, in terms of future work on DL-based MI detection, it is desirable to develop practical clinical decision support tools capable of being used both in and out of the hospital, like in figure 7. As can be seen in the setup of figure 7, wearable devices act as an interface between the patient and remote medical services. Another important weakness of DL is its black box behavior. To cover this weakness, studies have been conducted in the field of explainable AI algorithms (Tjoa and Guan 2020). Using these types of algorithms in the field of medicine will definitely have a bright future.

Additionally, further improvement and reliability of MI detection using DL is also a possible direction for future works. Furthermore, it is desirable to reduce the time of input signal preparation and preprocessing. Heart rate signals extracted from ECG can be used for MI detection (Jayachandran 2010, Loh *et al* 2022). The heart rate signals demand lower bandwidth, so using those yields a significant reduction in memory requirement. Alternatively, heart rate signals may be obtained from photoplethysmography signals (Loh *et al* 2022) acquired using wearable devices (e.g. wristwatch).



6. Conclusion

ECG signals are frequently used to screen for MI. On the other hand, manual ECG analysis is time-consuming and subject to bias. ML methods rely on handcrafted features based on ECG signals, whereas DL is capable of automatic feature extraction. We reviewed the methods based on ML and DL for MI diagnosis. To this end, several papers were collected based on search keywords. Thirty-one papers focused on ML methods and thirty-five on DL methods. According to the reviewed papers, DCNN models yield the highest accuracy for MI diagnosis in DL. As a result, many researchers have used DL methods in recent years. Nevertheless, as with any other method, DL has its drawbacks as well, which need urgent improvements in future work.

ORCID iDs

Javad Hassannataj Joloudari  <https://orcid.org/0000-0001-9374-2326>

Amir Mashmool  <https://orcid.org/0000-0002-1612-3094>

Hui Wen Loh  <https://orcid.org/0000-0003-3114-6523>

U Rajendra Acharya  <https://orcid.org/0000-0003-2689-8552>

References

- Acharya U R, Fujita H, Adam M, Lih O S, Sudarshan V K, Hong T J, Koh J E, Hagiwara Y, Chua C K and Poo C K 2017a Automated characterization and classification of coronary artery disease and myocardial infarction by decomposition of ECG signals: a comparative study *Inf. Sci.* **377** 17–29
- Acharya U R, Fujita H, Oh S L, Hagiwara Y, Tan J H and Adam M 2017b Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals *Inf. Sci.* **415** 190–8
- Acharya U R, Fujita H, Sudarshan V K, Oh S L, Adam M, Koh J E, Tan J H, Ghista D N, Martis R J and Chua C K 2016 Automated detection and localization of myocardial infarction using electrocardiogram: a comparative study of different leads *Knowl.-Based Syst.* **99** 146–56
- Alharthi A S, Yunus S U and Ozanyan K B 2019 Deep learning for monitoring of human gait: a review *IEEE Sens. J.* **19** 9575–91
- Ali F, El-Sappagh S, Islam S R, Kwak D, Ali A, Imran M and Kwak K-S 2020 A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion *Information Fusion* **63** 208–22
- Ansari S, Farzaneh N, Duda M, Horan K, Andersson H B, Goldberger Z D, Nallamothu B K and Najarian K 2017 A review of automated methods for detection of myocardial ischemia and infarction using electrocardiogram and electronic health records *IEEE Rev. Biomed. Eng.* **10** 264–98
- Arif M, Malagore I A and Afsar F A 2010 Automatic detection and localization of myocardial infarction using back propagation neural networks *2010 4th Int. Conf. on Bioinformatics and Biomedical Engineering (Piscataway, NJ) (IEEE)* pp 1–4

- Arif M, Malagore I A and Afsar F A 2012 Detection and localization of myocardial infarction using k-nearest neighbor classifier *J. Med. Syst.* **36** 279–89
- Baloglu U B, Talo M, Yildirim O, San Tan R and Acharya U R 2019 Classification of myocardial infarction with multi-lead ECG signals and deep CNN *Pattern Recognit. Lett.* **122** 23–30
- Banerjee S and Mitra M 2012 Cross wavelet transform based analysis of electrocardiogram signals *International Journal of Electrical, Electronics and Computer Engineering* **1** 88–92
- Boersma E, Mercado N, Poldermans D, Gardien M, Vos J and Simoons M L 2003 Acute myocardial infarction *Lancet* **361** 847–58
- Borisov A V, Syrkinina A G, Kuzmin D A, Ryabov V V, Boyko A A, Zaharova O, Zasedatel V S and Kistenev Y V 2021 Application of machine learning and laser optical-acoustic spectroscopy to study the profile of exhaled air volatile markers of acute myocardial infarction *J. Breath Res.* **15** 027104
- Bousseljot R, Kreiseler D and Schnabel A J B T B E 1995 *Nutzung der EKG-Signaldatenbank CARDIODAT der PTB über das Internet* **40** 317–8
- Canto J G, Shlipak M G, Rogers W J, Malmgren J A, Frederick P D, Lambrew C T, Ornato J P, Barron H V and Kiefe C I 2000 Prevalence, clinical characteristics, and mortality among patients with myocardial infarction presenting without chest pain *JAMA* **283** 3223–9
- Cao Y, Wei T, Zhang B, Lin N, Rodrigues J J, Li J and Zhang D 2021 ML-Net: multi-channel lightweight network for detecting myocardial infarction *IEEE Journal of Biomedical and Health Informatics* **25** 3721–31
- Chang P-C, Lin J-J, Hsieh J-C and Weng J 2012 Myocardial infarction classification with multi-lead ECG using hidden Markov models and Gaussian mixture models *Appl. Soft Comput.* **12** 3165–75
- Chen M, Shi X, Zhang Y, Wu D and Guizani M 2017 Deep features learning for medical image analysis with convolutional autoencoder neural network *IEEE Transactions on Big Data* **7** 750–8
- Chen Z, Lalonde A, Salomon M, Decourselle T, Pommier T, Qayyum A, Shi J, Perrot G and Couturier R 2022 Automatic deep learning-based myocardial infarction segmentation from delayed enhancement MRI *Comput. Med. Imaging Graph.* **95** 102014
- Creemers E E, Cleutjens J P, Smits J F and Daemen M J 2001 Matrix metalloproteinase inhibition after myocardial infarction: a new approach to prevent heart failure? *Circ. Res.* **89** 201–10
- Davenport T and Kalakota R 2019 The potential for artificial intelligence in healthcare *Future Healthcare Journal* **6** 94–8
- Degerli A, Zabihi M, Kiranyaz S, Hamid T, Mazhar R, Hamila R and Gabbouj M 2021 Early detection of myocardial infarction in low-quality echocardiography *IEEE Access* **9** 34442–53
- Diker A, Cömert Z, Avci E and Velappan S 2018 Intelligent system based on Genetic Algorithm and support vector machine for detection of myocardial infarction from ECG signals *2018 26th Signal Processing and Communications Applications Conf. (SIU) (Piscataway, NJ) (IEEE)* pp 1–4
- Dohare A K, Kumar V and Kumar R 2018 Detection of myocardial infarction in 12 lead ECG using support vector machine *Appl. Soft Comput.* **64** 138–47
- Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, Cui C, Corrado G, Thrun S and Dean J 2019 A guide to deep learning in healthcare *Nat. Med.* **25** 24–9
- Faust O, Hagiwara Y, Hong T J, Lih O S and Acharya U R 2018 Deep learning for healthcare applications based on physiological signals: a review *Comput. Methods Programs Biomed.* **161** 1–13
- Feng K, Pi X, Liu H and Sun K 2019 Myocardial infarction classification based on convolutional neural network and recurrent neural network *Applied Sciences* **9** 1–12
- Fu L, Lu B, Nie B, Peng Z, Liu H and Pi X 2020 Hybrid network with attention mechanism for detection and location of myocardial infarction based on 12-lead electrocardiogram signals *Sensors* **20** 1–24
- Garland J, Hu M, Duffy M, Kesha K, Glenn C, Morrow P, Stables S, Ondruschka B, Da Broi U and Tse R D 2021 Classifying microscopic acute and old myocardial infarction using convolutional neural networks *The American Journal of Forensic Medicine and Pathology* **42** 230–4
- Guo Y, Du G-Q, Shen W-Q, Du C, He P-N and Siuly S 2021 Automatic myocardial infarction detection in contrast echocardiography based on polar residual network *Comput. Methods Programs Biomed.* **198** 105791
- Gupta A, Huerta E, Zhao Z and Moussa I 2020 Deep learning for cardiologist-level myocardial infarction detection in electrocardiograms *European Medical and Biological Engineering Conf. 80 (Berlin)* (Springer) pp 341–55
- <https://physionet.org/content/mitdb/1.0.0/>, (accessed 2022)
- <https://physionet.org/content/ptbdb/1.0.0/>, (accessed 2022)
- <https://physionet.org/content/ptb-xl/1.0.1/>, (accessed 2022)
- Hammad M, Alkinani M H, Gupta B and Abd El-Latif A A 2021b Myocardial infarction detection based on deep neural network on imbalanced data *Multimedia Syst.* **1**–13
- Hammad M, Rajesh K N, Abdelatey A, Abdar M, Zomorodi-Moghadam M, San Tan R, Acharya U R, Plawiak J, Tadeusiewicz R and Makarenkov V 2021a Automated detection of Shockable ECG signals: a review *Inf. Sci.* **571** 580–604
- Han C and Shi L 2019 Automated interpretable detection of myocardial infarction fusing energy entropy and morphological features *Comput. Methods Programs Biomed.* **175** 9–23
- Han C and Shi L 2020 ML-ResNet: a novel network to detect and locate myocardial infarction using 12 leads ECG *Comput. Methods Programs Biomed.* **185** 105138
- Haraldsson H, Edenbrandt L and Ohlsson M 2004 Detecting acute myocardial infarction in the 12-lead ECG using Hermite expansions and neural networks *Artif. Intell. Med.* **32** 127–36
- He Z, Yuan Z, An P, Zhao J and Du B 2021 MFB-LANN: a lightweight and updatable myocardial infarction diagnosis system based on convolutional neural networks and active learning *Comput. Methods Programs Biomed.* **210** 106379
- Hedén B, Ohlin H, Rittner R and Edenbrandt L 1997 Acute myocardial infarction detected in the 12-lead ECG by artificial neural networks *Circulation* **96** 1798–802
- Huang T-H, Lee W-K, Wu C-C, Lee C-C, Lu C-F, Yang H-C, Lin C-Y, Chung W-Y, Wang P-S and Chen Y-L 2021 Detection of vestibular schwannoma on triple-parametric magnetic resonance images using convolutional neural networks *Journal of Medical and Biological Engineering* **41** 626–35
- Jahmunah V, Ng E, San T R and Acharya U R 2021 Automated detection of coronary artery disease, myocardial infarction and congestive heart failure using GaborCNN model with ECG signals *Comput. Biol. Med.* **134** 104457
- Jayachandran E 2010 Analysis of myocardial infarction using discrete wavelet transform *J. Med. Syst.* **34** 985–92
- Jian J-Z, Ger T-R, Lai H-H, Ku C-M, Chen C-A, Abu P A R and Chen S-L 2021 Detection of myocardial infarction using ECG and multi-scale feature concatenate *Sensors* **21** 1–17
- Jiang F, Jiang Y, Zhi H, Dong Y, Li H, Ma S, Wang Y, Dong Q, Shen H and Wang Y 2017 Artificial intelligence in healthcare: past, present and future *Stroke and Vascular Neurology* **2** 230–43

- Joloudari J H, Haderbadi M, Mashmool A, GhasemiGol M, Band S S and Mosavi A 2020 Early detection of the advanced persistent threat attack using performance analysis of deep learning *IEEE Access* **8** 186125–37
- Jordan MI and Mitchell T M 2015 Machine learning: Trends, perspectives, and prospects *Science* **349** 255–60
- Kayikcioglu İ, Akdeniz F, Köse C and Kayikcioglu T 2020 Time-frequency approach to ECG classification of myocardial infarction *Comput. Electr. Eng.* **84** 106621
- Ker J, Wang L, Rao J and Lim T 2017 Deep learning applications in medical image analysis *Ieee Access* **6** 9375–89
- Khatun S and Morshed B I 2017 Detection of myocardial infarction and arrhythmia from single-lead ECG data using bagging trees classifier *2017 IEEE Int. Conf. on Electro Information Technology (EIT) (Piscataway, NJ)* (IEEE) pp 520–4
- Kim Y-C, Kim K R and Choe Y H 2020 Automatic myocardial segmentation in dynamic contrast enhanced perfusion MRI using Monte Carlo dropout in an encoder-decoder convolutional neural network *Comput. Methods Programs Biomed.* **185** 105150
- Kora P and Kalva S R 2015 Improved Bat algorithm for the detection of myocardial infarction *SpringerPlus* **4** 1–18
- Kumar M, Pachori R B and Acharya U R 2017 Automated diagnosis of myocardial infarction ECG signals using sample entropy in flexible analytic wavelet transform framework *Entropy* **19** 1–14
- Lih O S, Jahmunah V, San T R, Ciaccio E J, Yamakawa T, Tanabe M, Kobayashi M, Faust O and Acharya U R 2020 Comprehensive electrocardiographic diagnosis based on deep learning *Artif. Intell. Med.* **103** 101789
- Lin Z, Gao Y, Chen Y, Ge Q, Mahara G and Zhang J 2020 Automated detection of myocardial infarction using robust features extracted from 12-lead ECG, *Signal Image and Video Processing* **14** 857–65
- Litjens G, Kooi T, Bejnordi B E, Setio A A A, Ciompi F, Ghafoorian M, Van Der Laak J A, Van Ginneken B and Sánchez C I 2017 A survey on deep learning in medical image analysis *Med. Image Anal.* **42** 60–88
- Liu B, Liu J, Wang G, Huang K, Li F, Zheng Y, Luo Y and Zhou F 2015 A novel electrocardiogram parameterization algorithm and its application in myocardial infarction detection *Comput. Biol. Med.* **61** 178–84
- Liu J, Zhang C, Zhu Y, Ristaniemi T, Parviainen T and Cong F 2020 Automated detection and localization system of myocardial infarction in single-beat ECG using Dual-Q TQWT and wavelet packet tensor decomposition *Comput. Methods Programs Biomed.* **184** 105120
- Liu W, Ji J, Chang S, Wang H, He J and Huang Q 2022 EvoMBN: evolving multi-branch networks on myocardial infarction diagnosis using 12-lead electrocardiograms *Biosensors* **12** 1–23
- Liu W, Wang F, Huang Q, Chang S, Wang H and He J 2019 MFB-CBRNN: a hybrid network for MI detection using 12-lead ECGs *IEEE journal of biomedical and health informatics* **24** 503–14
- Loh H W, Xu S, Faust O, Ooi C P, Barua P D, Chakraborty S, Tan R-S, Molinari F and Acharya U R 2022 Application of Photoplethysmography signals for Healthcare systems: an in-depth review *Comput. Methods Programs Biomed.* **216** 106677
- Lu H, Ong K and Chia P 2000 An automated ECG classification system based on a neuro-fuzzy system *Computers in Cardiology 2000 27 (Piscataway, NJ)* (IEEE) pp 387–90 (Cat. 00CH37163)
- Lui H W and Chow K L 2018 Multiclass classification of myocardial infarction with convolutional and recurrent neural networks for portable ECG devices *Informatics in Medicine Unlocked* **13** 26–33
- Lundervold A S and Lundervold A 2019 An overview of deep learning in medical imaging focusing on MRI *Zeitschrift für Medizinische Physik* **29** 102–27
- Mohammad M A, Olesen K K, Koul S, Gale C P, Rylance R, Jernberg T, Baron T, Spaak J, James S and Lindahl B 2022 Development and validation of an artificial neural network algorithm to predict mortality and admission to hospital for heart failure after myocardial infarction: a nationwide population-based study *The Lancet Digital Health* **4** e37–45
- Moody G B and Mark R G 1990 The MIT-BIH arrhythmia database on CD-ROM and software for use with it [1990] *Proc. Computers in Cardiology (Piscataway, NJ)* (IEEE) pp 185–8
- Moody G B and Mark R G 2001 The impact of the MIT-BIH Arrhythmia Database *IEEE Eng. Med. Biol. Mag.* **20** 45–50
- Natesan P and Gothai E 2020 Classification of multi-lead ECG signals to predict myocardial infarction using CNN *2020 Fourth Int. Conf. on Computing Methodologies and Communication (ICCMC) (Piscataway, NJ)* (IEEE) pp 1029–33
- Nosratabadi S, Mosavi A, Duan P, Ghamisi P, Filip F, Band S S, Reuter U, Gama J and Gandomi A H 2020 Data science in economics: comprehensive review of advanced machine learning and deep learning methods *Mathematics* **8** 1–25
- Panayides A S, Amini A, Filipovic N D, Sharma A, Tsafaris S A, Young A, Foran D, Do N, Golemati S and Kurc T 2020 AI in medical imaging informatics: current challenges and future directions *IEEE Journal of Biomedical and Health Informatics* **24** 1837–57
- Panchavati S, Lam C, Zelin N S, Pellegrini E, Barnes G, Hoffman J, Garikipati A, Calvert J, Mao Q and Das R 2021 Retrospective validation of a machine learning clinical decision support tool for myocardial infarction risk stratification *Healthcare Technology Letters* **8** 139–47
- Rai H M and Chatterjee K 2021 Hybrid CNN-LSTM deep learning model and ensemble technique for automatic detection of myocardial infarction using big ECG data *Applied Intelligence* **52** 5366–84
- Rai H M, Chatterjee K, Dubey A and Srivastava P 2021 Myocardial infarction detection using deep learning and ensemble technique from ECG signals *Proc. of Second Int. Conf. on Computing, Communications, and Cyber-Security 203 (Berlin)* (Springer) pp 717–30
- Rawat W and Wang Z 2017 Deep convolutional neural networks for image classification: a comprehensive review *Neural Comput.* **29** 2352–449
- Reasat T and Shahnaz C 2017 Detection of inferior myocardial infarction using shallow convolutional neural networks *2017 IEEE Region 10 Humanitarian Technology Conf. (R10-HTC) (Piscataway, NJ)* (IEEE) pp 718–21
- Reddy M, Edenbrandt L, Svensson J, Haisty W and Pahlm O 1992 Neural network versus electrocardiographer and conventional computer criteria in diagnosing anterior infarct from the ECG *Proc. Computers in Cardiology (Piscataway, NJ)* (IEEE) pp 667–70
- Ribeiro J M, Astudillo P, Backer O de, Budde R, Nuis R J, Goudzwaard J, Van Mieghem N M, Lumens J, Mortier P and Raso F M 2022 Artificial intelligence and transcatheter interventions for structural heart disease: a glance at the (near) future *Trends in Cardiovascular Medicine* **32** 153–9
- Safdarian N, Dabanloo N J and Attarodi G 2014 A new pattern recognition method for detection and localization of myocardial infarction using T-wave integral and total integral as extracted features from one cycle of ECG signal *J. Biomed. Sci. Eng.* **2014** 818–24
- Shahnawaz M B and Dawood H 2021 An effective deep learning model for automated detection of myocardial infarction based on ultrashort-term heart rate variability analysis *Mathematical Problems in Engineering* **2021** 1–13
- Sharifrazi D, Alizadehsani R, Joloudari J H, Shamshirband S, Hussain S, Sani Z A, Hasanzadeh F, Shoaibi A, Dehjangi A and Alinejad-Rokny H 2022 CNN-KCL: Automatic Myocarditis Diagnosis using Convolutional Neural Network Combined with K-means Clustering **19** 2381–402
- Sharma L, Tripathy R and Dandapat S 2015 Multiscale energy and eigenspace approach to detection and localization of myocardial infarction *IEEE Trans. Biomed. Eng.* **62** 1827–37
- Sharma L D and Sunkaria R K 2018 Inferior myocardial infarction detection using stationary wavelet transform and machine learning approach *Signal, Image and Video Processing* **12** 199–206

- Shen D, Wu G and Suk H-I 2017 Deep learning in medical image analysis *Annu. Rev. Biomed. Eng.* **19** 221–48
- Shi F, Wang J, Shi J, Wu Z, Wang Q, Tang Z, He K, Shi Y and Shen D 2020 Review of artificial intelligence techniques in imaging data acquisition, segmentation, and diagnosis for COVID-19 *IEEE Rev. Biomed. Eng.* **14** 4–15
- Strothoff N and Strothoff C 2019 Detecting and interpreting myocardial infarction using fully convolutional neural networks *Physiol. Meas.* **40** 015001
- Sulthana A R and Jaithunbi A 2022 Varying combination of feature extraction and modified support vector machines based prediction of myocardial infarction *Evolving Systems* **1**–18
- Sun L, Lu Y, Yang K and Li S 2012 ECG analysis using multiple instance learning for myocardial infarction detection *IEEE Trans. Biomed. Eng.* **59** 3348–56
- Sun Y, Xue B, Zhang M, Yen G G and Lv J 2020 Automatically designing CNN architectures using the genetic algorithm for image classification *IEEE Transactions on Cybernetics* **50** 3840–54
- Tadesse G A, Javed H, Weldemariam K, Liu Y, Liu J, Chen J and Zhu T 2021a DeepMI: deep multi-lead ECG fusion for identifying myocardial infarction and its occurrence-time *Artif. Intell. Med.* **121** 102192
- Tadesse G A, Weldemariam K, Javed H, Liu Y, Liu J, Chen J and Zhu T 2021b *Discriminant Knowledge Extraction from Electrocardiograms for Automated Diagnosis of Myocardial Infarction, Knowledge Management and Acquisition for Intelligent Systems: 17th Pacific Rim Knowledge Acquisition Workshop, PKAW 2020 (Yokohama, Japan, January 7–8, 2021)* (Springer Int. Publishing) pp 70–82 Proc. 17
- Than M P, Pickering J W, Sandoval Y, Shah A S, Tsanas A, Apple F S, Blankenberg S, Cullen L, Mueller C and Neumann J T 2019 Machine learning to predict the likelihood of acute myocardial infarction *Circulation* **140** 899–909
- Tjoa E and Guan C 2020 A survey on explainable artificial intelligence (xai): toward medical xai *IEEE Trans Neural Netw. Learn. Syst.* **32** 4793–813
- Tobore I, Li J, Yuhang L, Al-Handarish Y, Kandwal A, Nie Z and Wang L 2019 Deep learning intervention for health care challenges: some biomedical domain considerations *JMIR mHealth and uHealth* **7** e11966
- Tripathy R K, Bhattacharyya A and Pachori R B 2019 A novel approach for detection of myocardial infarction from ECG signals of multiple electrodes *IEEE Sens. J.* **19** 4509–17
- Valizadeh G, Mofrad F B and Shalbaf A 2021 Parametric-based feature selection via spherical harmonic coefficients for the left ventricle myocardial infarction screening *Med. Biol. Eng. Comput.* **5** 1261–83
- Wagner P, Strothoff N, Boussejot R-D, Kreiseler D, Lunze F I, Samek W and Schaeffter T 2020a PTB-XL, a large publicly available electrocardiography dataset *Scientific Data* **7** 1–15
- Wagner P, Strothoff N, Boussejot R-D, Kreiseler D, Lunze F I, Samek W and Schaeffter T 2020b PTB-XL, a large publicly available electrocardiography dataset *Scientific Data* **7** 1–15
- Wallert J, Tomasoni M, Madison G and Held C 2017 Predicting two-year survival versus non-survival after first myocardial infarction using machine learning and Swedish national register data *BMC Med. Inf. Decis. Making* **17** 1–11
- Wang K-N, Yang X, Miao J, Li L, Yao J, Zhou P, Xue W, Zhou G-Q, Zhuang X and Ni D 2022 AWSnet: an auto-weighted supervision attention network for myocardial scar and edema segmentation in multi-sequence cardiac magnetic resonance images *Med. Image Anal.* **77** 102362
- Wang Q, Zhao C, Qiang Y, Zhao Z, Song K and Luo S 2021 Multitask interactive attention learning model based on hand images for assisting chinese medicine in predicting myocardial infarction *Computational and Mathematical Methods in Medicine* **2021**
- Xiong P, Xue Y, Zhang J, Liu M, Du H, Zhang H, Hou Z, Wang H and Liu X 2021 Localization of myocardial infarction with multi-lead ECG based on DenseNet *Comput. Methods Programs Biomed.* **203** 106024
- Yadav S S, More S B, Jadhav S M and Sutar S R 2021 Convolutional neural networks based diagnosis of myocardial infarction in electrocardiograms 2021 *Int. Conf. on Computing, Communication, and Intelligent Systems (ICCCIS) (Piscataway, NJ)* (IEEE) pp 581–6
- Yang H, Kan C, Liu G and Chen Y 2013 Spatiotemporal differentiation of myocardial infarctions *IEEE Trans. Autom. Sci. Eng.* **10** 938–47
- Yu K-H, Beam A L and Kohane I S 2018 Artificial intelligence in healthcare *Nat. Biomed. Eng.* **2** 719–31
- Zeng W, Yuan J, Yuan C, Wang Q, Liu F and Wang Y 2020 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.* **101848**
- Zhang G, Si Y, Wang D, Yang W and Sun Y 2019b Automated detection of myocardial infarction using a gramian angular field and principal component analysis network *IEEE Access* **7** 171570–83
- Zhang J, Lin F, Xiong P, Du H, Zhang H, Liu M, Hou Z and Liu X 2019a Automated detection and localization of myocardial infarction with staked sparse autoencoder and treebagger *IEEE Access* **7** 70634–42
- Zheng H, Wang H, Nugent C and Finlay D 2006 Supervised classification models to detect the presence of old myocardial infarction in body surface potential maps 2006 *Computers in Cardiology (Piscataway, NJ)* (IEEE) pp 265–8 (<https://ieeexplore.ieee.org/abstract/document/4511839>) 978-1-4244-2532-7
- Zheng J, Zhang J, Danioko S, Yao H, Guo H and Rakovski C 2020 A 12-lead electrocardiogram database for arrhythmia research covering more than 10,000 patients *Scientific Data* **7** 1–8