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

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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 (LTML). 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 LTML 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 staked 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 were 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 ± 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 plots 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 | Performancea |
|-----|------------------|--------------|------------|---------------|------------------------------------------------------------------------------------------------|--------------------|--------------|
| 1   | (Reddy et al 1992) | ANN          | Yes        | NC            | Leads: V2-V4 Subjects: 272 MI, 479 Normal                                                                 | inter-beat          | ACC:79.00    |
| 2   | (Hedén et al 1997) | ANN          | Yes        | 8-fold CV     | Leads: 12 leads Subjects: 1120 MI, 10452 Normal from PTB database                                      | inter-beat          | ACC:86.30    |
| 3   | (Lu et al 2000)   | Neuro-fuzzy classifier | No        | NC            | Leads: 12 leads, Subjects: 20 normal, 104 MI                                                                 | inter-beat          | ACC:89.40    |
| 4   | (Haraldsson et al 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:94.30    |
| 5   | (Zheng et al 2006) | SVM          | No         | 10-fold CV    | Leads: 192-lead body surface potential maps Subjects: 57 MI, 59 Normal from PTB database                                                                 | inter-beat          | ACC:88.20    |
| 6   | (Arif et al 2010) | BPNN + PCA   | No         | NC            | Leads: 12 leads Subject: 148 MI and 52 Normal from PTB database                                                                                       | inter-beat          | ACC:93.70    |
| 7   | (Sun et al 2012)  | LTMIL + SVM  | No         | 10-fold CV    | Leads: 12 leads Subject: 369 MI, 79 Normal from PTB database                                                                                       | inter-beat          | ACC:90.00    |
| 8   | (Arif et al 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    |
| 9   | (Chang et al 2012) | HMMs + GMMs  | No         | NC            | Leads: Leads V1-V4 Subjects: 1129 samples of heartbeats; 582 MI, 547 Normal                                                                          | inter-beat          | ACC:85.71    |
| 10  | (Safdarian et al 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 Subjects: 290 subjects and 549 records from PTB database                                                                                  | inter-beat          | ACC:98.90    |
| No. | Author, Year       | Methods                        | End-to-End | No. K-fold CV | Dataset (No. of leads, Subjects)                                                                 | Division Solutions | Performance^a |
|-----|--------------------|--------------------------------|------------|---------------|-------------------------------------------------------------------------------------------------|--------------------|---------------|
| 12  | (Sharma et al. 2013) | SVM-RBF                        | No         | 5-fold CV    | Subjects: 148 MI, 52 Normal from PTB database                                                    | Leads: 12 leads   | Spe: 92.20    |
|     |                    |                                |            |               |                                                                                                 |                    | Sen: 93.34    |
| 13  | (Acharya et al. 2016) | DWT coefficients + KNN        | No         | 10-fold CV   | Subjects: 52 Normal, 148 MI from PTB database                                                   | Leads: Lead V5     | Spe: 99.00    |
|     |                    |                                |            |               |                                                                                                 |                    | Sen: 93.00    |
| 14  | (Acharya et al. 2017a) | DCT coefficients + KNN        | No         | 10-fold CV   | Subjects: 52 normal, 148 MI from PTB database                                                   | Leads: Lead II     | Spe: 96.27    |
|     |                    |                                |            |               |                                                                                                 |                    | Sen: 99.45    |
| 15  | (Kumar et al. 2017) | LS-SVM-RBF                     | No         | 10-fold CV   | Subjects: 52 Normal and 148 MI from PTB database                                                | Leads: Lead II     | Spe: 98.50    |
|     |                    |                                |            |               |                                                                                                 |                    | Sen: 99.70    |
| 16  | (Khatun and Morshed 2017) | BTs                            | No         | 10-fold CV   | Subjects: 79 normal, 346 MI from PTB database                                                   | Leads: 12 leads    | Spe: 98.12    |
|     |                    |                                |            |               |                                                                                                 |                    | Sen: 99.62    |
| 17  | (Acharya et al. 2017a) | CWT-based control + KNN       | No         | 10-fold CV   | Subjects: 148 MI, 52 Normal from PTB database                                                   | Leads: 12 leads    | Spe: 99.32    |
|     |                    |                                |            |               |                                                                                                 |                    | Sen: 100.00   |
| 18  | (Dohare et al. 2018) | SVM + PCA                      | No         | 10-fold CV   | Subjects: 60 MI, 60 Normal from PTB database                                                   | Leads: 12 leads    | Spe: 99.24    |
|     |                    |                                |            |               |                                                                                                 |                    | Sen: 99.93    |
| 19  | (Diker et al. 2018) | GA + SVM                       | No         | 10-fold CV   | Subjects: 549 records from 290 subjects                                                       | Leads: 12 leads    | Spe: 100.00   |
|     |                    |                                |            |               |                                                                                                 |                    | Sen: 96.66    |

^a Performance values: ACC: accuracy, Pre: precision, Spe: specificity, Sen: sensitivity, F1: F1 score.
| No. | Author, Year       | Methods                          | End-to-End | No. K-fold CV | Dataset (No. of leads, Subjects)                                                                                           | Division Solutions       | Performance³ |
|-----|-------------------|----------------------------------|------------|---------------|--------------------------------------------------------------------------------------------------------------------------|--------------------------|---------------|
| 20  | (Sharma and       | SWT + SVM                        | No         | 10-fold CV    | Subjects: 148 MI, 52 Normal from PTB database                                                                          | inter-beat               | ACC: 98.44    |
|     | Sunkaria 2018)    |                                  |            |               | Leads: Lead-II, III and aVF                                                                                             |                          | Spe: 86.97    |
|     |                   |                                  |            |               | Subjects: 148 MI, 52 Normal from PTB database                                                                          |                          | Sen: 88.67    |
| 21  | (Han and          | SVM-RBF, BPNN, Bagging          | No         | 10-fold CV    | Subjects: 148 MI, 52 Normal from PTB database                                                                          | inter-patient            | ACC: 99.75    |
|     | Shi 2019)         |                                  |            |               | Leads: 12 leads                                                                                                         |                          | Pre: 98.41    |
|     |                   |                                  |            |               | Subjects: 148 MI, 52 Normal from PTB database                                                                          |                          | Spe: 98.29    |
|     |                   |                                  |            |               | ACC: 98.35                                                                                                             |                          | Sen: 99.35    |
| 22  | (Zhang et al      | SAE + TB                         | Yes        | 10-fold CV    | Subjects: 148 MI, 52 Normal from PTB database                                                                          | inter-patient            | ACC: 99.90    |
|     | 2019a)            |                                  |            |               | Leads: Lead II                                                                                                         |                          | Spe: 99.52    |
|     |                   |                                  |            |               | Subjects: 148 MI, 52 Normal from PTB database                                                                          |                          | Sen: 99.98    |
| 23  | (Zeng et al 2020) | RBF- neural network              | No         | 10-fold CV    | Subjects: 148 MI, 52 Normal from PTB database                                                                          | inter-beat               | ACC: 97.98    |
|     |                   |                                  |            |               | Leads: 15 leads                                                                                                         |                          | Pre: 99.45    |
|     |                   |                                  |            |               | Subjects: 148 MI, 52 Normal from PTB database                                                                          |                          | Spe: 97.44    |
|     |                   |                                  |            |               | ACC: 97.44                                                                                                             |                          | Sen: 98.09    |
| 24  | (Kayikcioglu et al| Weighted KNN                     | No         | 10-fold CV    | 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    |
|     | 2020)             |                                  |            |               | Leads: Leads V1-V5                                                                                                      |                          | Spe: 98.15    |
|     |                   |                                  |            |               | ACC: 94.23                                                                                                             |                          | Sen: 95.72    |
| 25  | (Liu et al 2020)  | Dual-QTQWT + DWPT + MPCA + TB    | No         | 10-fold CV    | Subjects: 78 Normal, 328 MI from PTB database                                                                          | inter-beat               | ACC: 97.46    |
|     |                   |                                  |            |               | Leads: 12 leads and 3 Frank leads (VX, VY, VZ)                                                                          |                          | F1: 95.30     |
|     |                   |                                  |            |               | Subjects: 78 Normal, 328 MI from PTB database                                                                          |                          | Spe: 90.26    |
|     |                   |                                  |            |               | ACC: 97.46                                                                                                             |                          | Sen: 99.09    |
| 26  | (Lin et al 2020)  | KNN                              | No         | 10-fold CV    | Subjects: 148 MI and 52 Normal from PTB database                                                                        | inter-beat               | ACC: 99.57    |
|     |                   |                                  |            |               | Leads: 12 Leads                                                                                                         |                          | Spe: 98.79    |
|     |                   |                                  |            |               | Subjects: 148 MI and 52 Normal from PTB database                                                                        |                          | Sen: 99.82    |
| 27  |                   |                                  | No         |                | 40 cine-MRI                                                               | inter-beat               | ACC: 97.5     |

³Accuracy, Sensitivity, and Specificity.
Table 1. (Continued.)

| No. | Author, Year          | Methods                                      | End-to-End | No. K-fold CV | Dataset (No. of leads, Subjects)                                                                 | Division Solutions | Performance^a |
|-----|-----------------------|----------------------------------------------|------------|---------------|------------------------------------------------------------------------------------------------|--------------------|---------------|
| 28  | (Shahnawaz and Dawood 2021) | ANN                                          | Yes        | 10-fold CV    | Leads: single lead Subjects: 148 MI, 52 Normal from PTB database                                  | SVM/KNN/RF         | Spe: 98.10    |
|     |                       |                                              |            |               |                                                                                               | inter-beat         | Sen: 100.00   |
|     |                       |                                              |            |               |                                                                                               | ACC: 99.10         | F1: 99.00     |
| 29  | (Panchavati et al 2021) | Gradient boosted tree model                  | No         | 3-fold CV     | Subjects: 253 MI, 1600 Normal, Electronic health records (age, glucose, systolic/diastolic blood pressure, etc) | SVM/KNN/RF         | Spe: 70.00    |
|     |                       |                                              |            |               |                                                                                               | inter-beat         | Sen: 87.00    |
|     |                       |                                              |            |               |                                                                                               | ACC: 94.03         | AUC: 87.00    |
| 30  | (Sulthana and Jaithunbi 2022) | Probabilistic PCA + multi-linear regression + RBF based SVMs | No         | 5-fold CV     | 517 tuples with 20 attributes, Clinical tests                                               | SVM/KNN/RF         | Pre: 26.00    |
|     |                       |                                              |            |               |                                                                                               | inter-beat         | 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.
| No. | Author, Year     | Methods                        | End-to-End | No. K-fold CV | Dataset (No. of leads, Subjects)                                                                 | Division Solution | Performancea |
|-----|------------------|--------------------------------|------------|---------------|-------------------------------------------------------------------------------------------------|-------------------|--------------|
| 1   | (Acharya et al 2017b) | DCNN                           | Yes        | 10-fold CV    | Leads: Lead II Subjects: 148 MI, 52 Normal from PTB database                                    | inter-beat        | ACC: 95.22   |
| 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   |
| 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        | ACC: 97.70   |
| 4   | (Baloglu et al 2019) | DCNN                           | Yes        | kNC           | Leads: lead V4 Subjects: 52 Normal, 148 MI from PTB database                              | inter-beat        | ACC: 99.78   |
| 5   | (Tripathy et al 2019) | DL-LSSVM                       | No         | 5-fold CV     | Leads: 12 leads Subjects: 148 MI, 52 Normal from PTB database                                | inter-beat        | ACC: 99.97   |
| 6   | (Zhang et al 2019b)  | GADF + PCANet + Linear SVM     | No         | 5-fold CV     | Leads: Lead II Subjects: 148 MI, 52 Normal from PTB database                               | inter-patient     | ACC: 99.49   |
| 7   | (Feng et al 2019)    | DCNN + LSTM                    | Yes        | 10-fold CV    | Leads: Lead I Subjects: 148 MI, 52 Normal from PTB database                               | inter-beat        | ACC: 95.40   |
| 8   | (Liu et al 2019)     | MFB-CBRNN + BLSTM              | Yes        | 5-fold CV     | Leads: 12 leads Subjects: 148 MI, 52 Normal from PTB database                          | inter-patient     | ACC: 99.90   |
### Table 2. (Continued.)

| No. | Author, Year                  | Methods                  | End-to-End | No. K-fold CV | Dataset (No. of leads, Subjects)                                                                 | Division Solution | Performance* |
|-----|-------------------------------|--------------------------|------------|---------------|-----------------------------------------------------------------------------------------------|-------------------|--------------|
| 9   | (Strodthoff and Strodthoff 2019) | DCNN-FC                  | Yes        | 10-fold CV    | Leads: 12 leads Subjects: 127 MI, 52 Normal                                                  |                  |              |
| 10  | (Gupta et al 2020)           | DCNNQuak                 | Yes        | 100-fold CV   | Leads: 12 leads along with 3 Frank leads Subjects: 52 Normal, 148 MI from PTB database         |                  |              |
| 11  | (Han and Shi 2020)           | ML-ResNet                | Yes        | 5-fold CV     | Leads: 12 leads Subjects: 52 Normal, 113 MI from PTB database                                 |                  |              |
| 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 |                  |              |
| 13  | (Natesan and Gothai 2020)    | DCNN + DA                | Yes        | NC            | Leads: 12 leads Subjects: 148 MI, 52 Normal from PTB database                                |                  |              |
| 14  | (Fu et al 2020)              | MLA-DCNN-BiGRU           | Yes        | 5-fold CV     | Leads: 12 leads Subjects: 148 MI, 52 Normal from PTB database                                |                  |              |
| 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 |                  |              |
| 16  | (Jahmunah et al 2021)        | DCNN                     | Yes        | 10-fold CV    | Leads: Lead II Subjects: 148 MI, 92 Normal from PTB database                                 |                  |              |

*Spe: Specificity, Sen: Sensitivity, ACC: Accuracy, Pre: Precision, F1: F1 Score, AUC: Area Under the Curve.
| No. | Author, Year | Methods | End-to-End | No. K-fold CV | Dataset (No. of leads, Subjects) | Division | Solution | Performancea |
|-----|--------------|---------|------------|--------------|---------------------------------|---------|----------|-------------|
| 17  | (Garland et al 2021) | InceptionResNet v2 | Yes | 5-fold CV | 150 images: 50 Normal, 50 Acute MI, and 50 Old MI, Histology slides | inter-beat | ACC: 100.00 | F1: 100.00 |
| 18  | (Tadesse et al 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 |
|     |              |         |            |              |                                 |         |          |             |
|     |              |         |            |              |                                 |         |          |             |
| 19  | (Jian et al 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 | ACC: 95.76 |
| 20  | (Wang et al 2021) | Multitask attention learning model | Yes | NC | 2414 hand images from 301 patients (182 males and 119 females), | inter-beat | ACC: 82.06 |
|     |              |         |            |              |                                 |         |          |             |
|     |              |         |            |              |                                 |         |          |             |
| 21  | (Rai and Chatterjee 2021) | DCNN-LSTM + ensemble technique | Yes | NC | Leads: Lead IIs: 52 Normal, 148 MI from PTB database; 47 subjects from MIT-BIH arrhythmia database | inter-beat | ACC: 99.89 |
|     |              |         |            |              |                                 |         |          |             |
|     |              |         |            |              |                                 |         |          |             |

*a Performance metrics: Spe = Specificity, Sen = Sensitivity, ACC = Accuracy, F1 = F1 Score, AUC = Area Under the Curve.*
| No. | Author, Year     | Methods                                         | End-to-End | No. K-fold CV | Dataset (No. of leads, Subjects)                                                                 | Division Solution | Performance* |
|-----|------------------|-------------------------------------------------|------------|---------------|-----------------------------------------------------------------------------------------------|-------------------|--------------|
| 22  | (Hammad et al 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 et al 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   |
|     |                  |                                                 |            |               |                                                                                               |                   | Spe: 99.40   |
|     |                  |                                                 |            |               |                                                                                               |                   | Sen: 96.86   |
|     |                  |                                                 |            |               |                                                                                               |                   | F1: 96.87    |
| 24  | (Yadav et al 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 et al 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 et al 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 et al 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 et al 2020) | inter-beat        | Pre: 83.00   |
|     |                  |                                                 |            |               |                                                                                               |                   | Spe: 95.10   |
|     |                  |                                                 |            |               |                                                                                               |                   | Sen: 95.10   |
|     |                  |                                                 |            |               |                                                                                               |                   | F1: 88.60    |
|     |                  |                                                 |            |               |                                                                                               |                   | AUC: 97.70   |
| No. | Author, Year | Methods | End-to-End | K-fold CV | Dataset (No. of leads, Subjects) | Division Solution | Performance* |
|-----|--------------|---------|------------|-----------|----------------------------------|-------------------|--------------|
| 28  | Guo et al 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 |
| 29  | Xiong et al 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 | ACC: 99.87; Spe: 99.98; Sen: 99.84 |
| 30  | Cao et al 2021 | DCNN-based multichannel lightweight model | Yes | 10-fold CV | Leads: V2, V3, V5, aVL; Subjects: 147 MI, 53 Normal from PTB database | inter-patient | ACC: 96.65; Spe: 97.72; Sen: 94.30; AUC: 96.71 |
| 31  | Borisov et al 2021 | Linear SVM + PCA | No | NC | Leads: 12 leads; 30 MI, 42 normal | inter-beat | NC |
| 32  | Chen et al 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 et al 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 | ACC: 97.11; Pre: 98.01; Spe: 90.20; Sen: 98.53; F1: 98.30; Based on PTB database: ACC: 90.10; 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* |
|-----|--------------|---------|------------|---------------|----------------------------------|-------------------|--------------|
| 34  | (Wang et al 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  
Jaccard coefficient: 57.70  
Hausdorff Distance: 14.12  
Acc: 99.06  
Pre: 99.14  
Spe: 98.65  
Sen: 99.33  
F1: 99.24  
G-Mean: 98.99 |
| 35  | (Wang et al 2022) | GAN + DCNN | Yes | 5-fold CV | Leads: Lead I  
Subjects: 52 Normal, 148 MI from PTB database | inter-beat | |

* 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, Spec: Specificity, Ppv: Positive Predictive Value, Pre: Precision, AUC: Area under the Curve, F1: F1-score, G-Mean: Geometric Mean, NC: not considered.
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.

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