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Abstract: Myocardial infarction disease (MID) is caused to the rapid progress of undiagnosed coronary artery disease (CAD) that indicates the injury of a heart cell by decreasing the blood flow to the cardiac muscles. MID is the leading cause of death in middle-aged and elderly subjects all over the world. In general, raw Electrocardiogram (ECG) signals are tested for MID identification by clinicians that is exhausting, time-consuming, and expensive. Artificial intelligence-based methods are proposed to handle the problems to diagnose MID on the ECG signals automatically. Hence, in this survey paper, artificial intelligence-based methods, including machine learning and deep learning, are review for MID diagnosis on the ECG signals. Using the methods demonstrate that the feature extraction and selection of ECG signals required to be handcrafted in the ML methods. In contrast, these tasks are explored automatically in the DL methods. Based on our best knowledge, Deep Convolutional Neural Network (DCNN) methods are highly required methods developed for the early diagnosis of MID on the ECG signals. Most researchers have tended to use DCNN methods, and no studies have surveyed using artificial intelligence methods for MID diagnosis on the ECG signals.

Keywords: Myocardial Infarction Disease, Electrocardiogram, Machine learning, Deep learning, deep convolutional neural network, Diagnosis

1. Introduction

A Myocardial Infarction Disease (MID) is known as a Heart attack commonly [1-5], in the health care environment, which its symptoms, is damage to the heart cells due to lack of oxygen to the blood in the heart vessels, and there is a loss of blood supply to the heart. If the heart attack is not diagnosed in time, it consequences to physical disabilities in the left ventricle of the heart, which eventually leads to Congestive Heart Failure (CHF). Heart failure is the disease that the heart cannot pump blood around the body efficiently because the heart muscle is too weak to pump blood. Also in very acute heart conditions, can lead to the death of individuals with these symptoms. When Coronary Artery

Disease (CAD) is not diagnosed correctly, it progresses rapidly and leads to MID [6] as blood flow to the heart muscle decreases [7]. For example, the annual occurrence of Clinical centers reception for critical MID places between 90 and 312 per 100 000 inhabitants in Europe [8]. The image of healthy and MID subjects is shown in Figure 1 [9, 10].
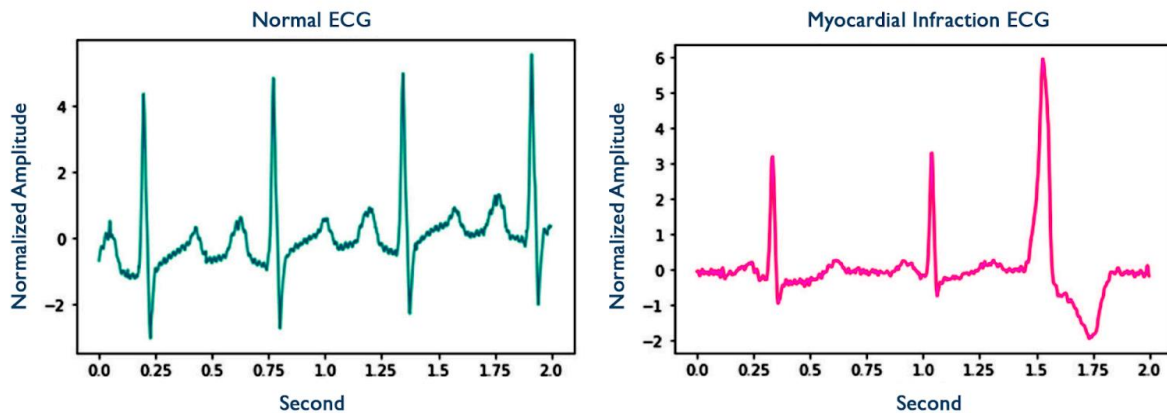

Figure 1. Typical ECG signals of Normal and MID subjects.

Based on Figure 1, most of the researchers used the Physikalisch-Technische Bundesanstalt (PTB) database for MID diagnosis. The records of the database are contained of twelve leads ECG and three Frank signals that are commentated by professional cardiologists. These signals are simultaneously recorded. There are 312 MID and 80 normal records from 113 MI patients and 52 HC patients, respectively, which is digitized at 1000Hz, with 16-bit resolution over a range of ±16.384 mV [11-13].
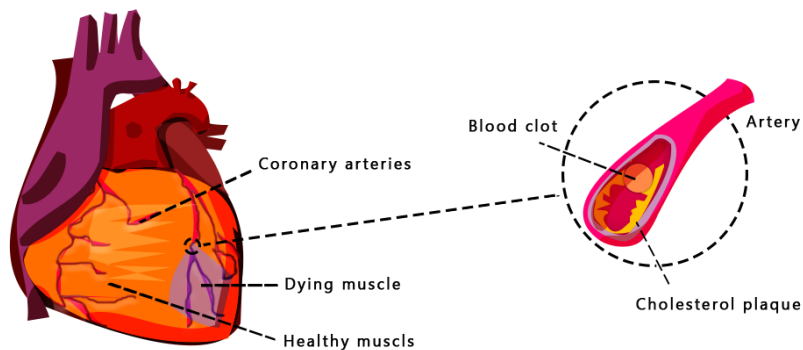Moreover, an illustration of MID is shown in Figure 3.

Figure 2. An illustration of MID.

Based on Figure 2, when one of the coronary arteries (right coronary artery, right coronary artery) becomes completely blocked, the MID is caused [14, 15].
The most common system of diagnosing heart disease, especially CAD and MID, is the electrocardiogram (ECG) [16-18]. If the condition is not diagnosed correctly, during testing and individuals are not treated in time, it can lead to CHF.
Therefore, it is essential to apply new methods and technologies based on intelligent decision-making of disease diagnosis. One solution is using Artificial Intelligence (AI)-based methods in healthcare [19-22]. In particular, healthcare researchers try to design and imbed a computer-based diagnostic system using AI methods that can both diagnose on time and distinguish MID subjects from healthy subjects with a high accuracy. As the latest scientific achievement for the early diagnosis of diseases based on images and medical signals, the DL follows ML methods. The difference between machine learning [23] and deep learning [24] is specified in terms of feature extraction and input data classification so that in machine learning, feature extraction and classification operations are performed

separately. In contrast, these operations are conducted automatically and hierarchical in deep learning. The difference between machine learning and deep learning methods is shown in Figure 3 [25].
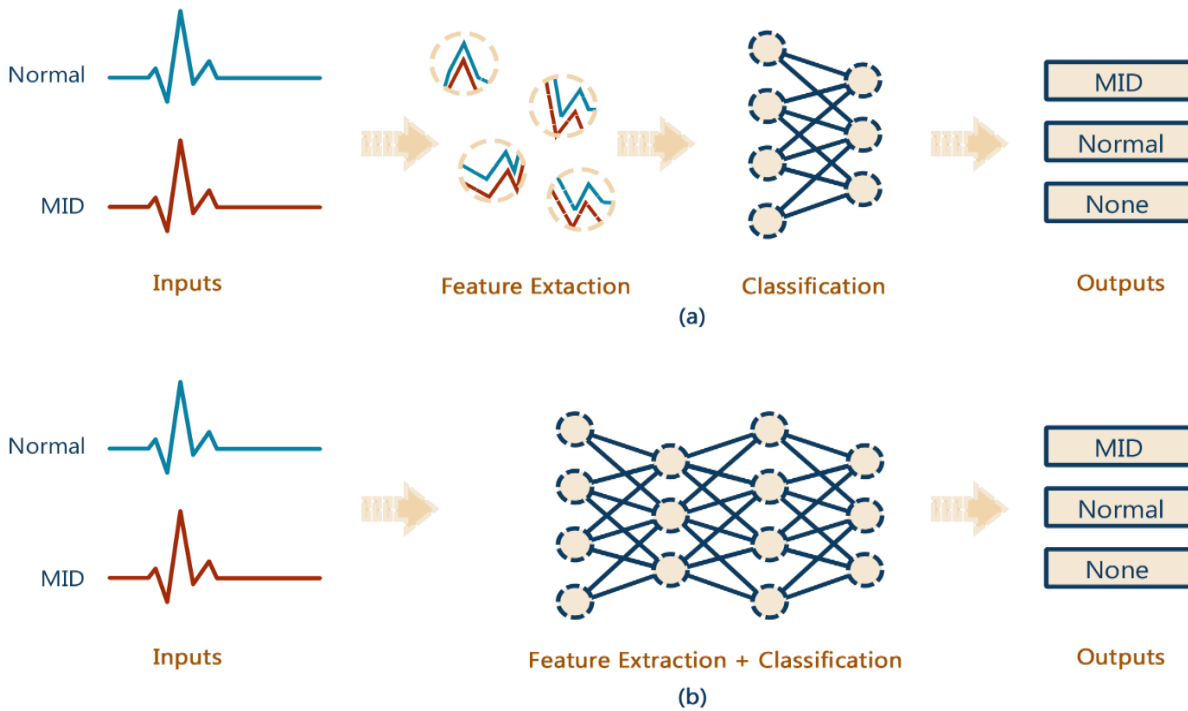

Figure 3. The difference between ML and DL.

The DL is a model of learning based on the representation that the model trains and builds intrinsic features of consecutive hidden layers of neurons. In other words, the countless hidden layers of Artificial Neural Network (ANN) structure are the reason for calling it "deep learning" [26].

In general, the ANN model is derived from the structure of a human biological brain. This model includes an input layer, zero to three hidden layers as the middle layers, and an output layer. The Conventional ANN structure is presented in Figure 4.
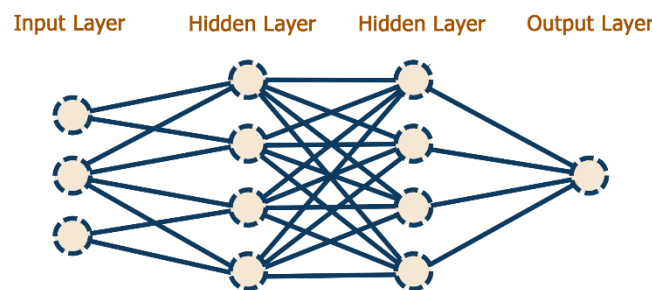

Figure 4. The Conventional ANN structure.

According to Figure 4, each neuron is joined to one another in the successive layer using an interconnection. Dendrites (input pulses), axon branch (output), a neuron (soma), cell nucleus (activation function), and synapses (weights) make a neural cell. The activation function in the artificial neural cells performs as a nucleus of a neuron that the input signals and its correlated weights from dendrites and synapses. Since the ANN structure is amenable to shift deviation, it may cause unpleasant effects in the classification performance. A model was developed called the Deep Convolutional Neural Network (DCNN), to enhance the capability of the ANN model with the number of ten to hundreds of hidden layers [27]. The state of the art of early diagnosis of diseases, the DCNN method has been known

as a crucial DL method on images and medical signals [27-35]. The Conventional DCNN structure is represented in Figure 5.
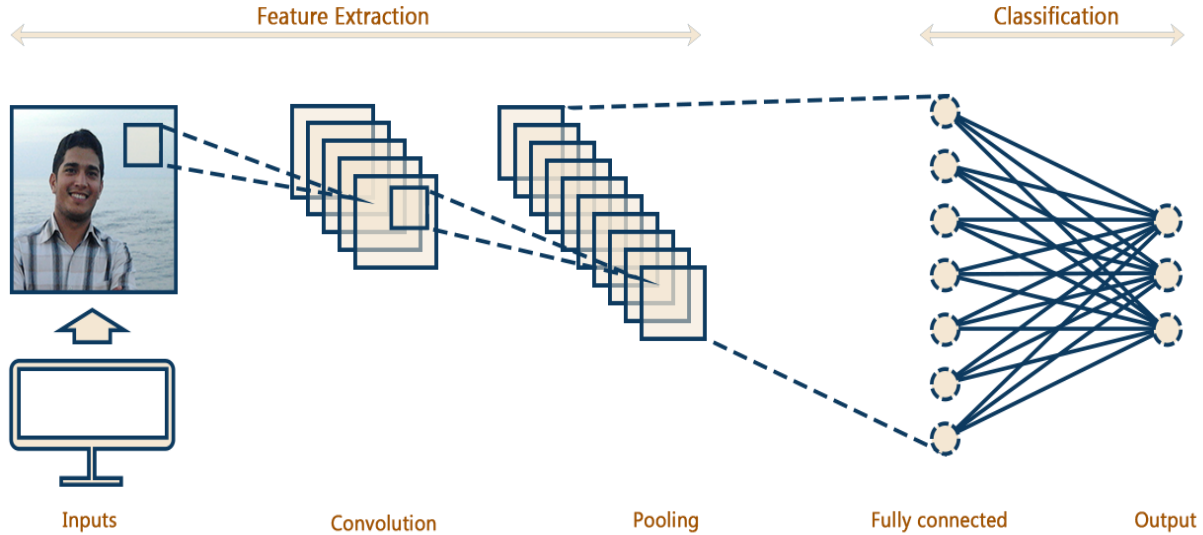

Figure 5. The Conventional DCNN structure [36].

Based on Figure 5, the DCNN method is widely used in learning applications based on an image set. Due to the automatic feature extraction mechanism of DCNN, helpful information can be found in the training sample. By using several convolutional, pooling, and fully-connected layers, DCNN is generally designed. The feature extraction is performed by convolving the input with convolutional kernels. The Pooling layer can decrease the computational complexity of the network without significant variation in the resolution of the feature map. Usually, in DCNN, by increasing the number of layers, the size of the pooling layers reduces. The max-pooling and average pooling are well-known as pooling layers. The last layer of the DCNN is called fully-connected neurons or fully-connected layers used to classify data. The classes are recognized using a classifier in the fully-connected layer.

Recently, studies have been conducted to diagnose MID using artificial intelligence-based methods, which we review in the current survey paper. Hence, the survey considers two categories of MID diagnosis methods: ML-based and DL-based.

The rest of the survey sections are as follows: A systematic literature review is provided for diagnosing the MID in Section 2. Section 3 describes the results and discussion. Conclusions and open research paths will be presented in Section 4. In the following, the terminologies are expressed in Table 1.

Table 1. Terminologies

Myocardial Infarction Disease (MID)	Genetic Algorithm (GA)
Heart Failure (CHF)	Fold-Cross Validation (FCV)
Coronary Artery Disease (CAD)	Sparse Autoencoder (SAE)
Physikalisch-Technische Bundesanstalt (PTB)	Tree Bagger (TB)
Electrocardiogram (ECG)	Dual-Q Tunable Q-factor Wavelet Transformation (Dual-Q TQWT)
Artificial Intelligence (AI)	Stationary Wavelet Transform (SWT)
Machine Learning (ML)	Recurrent Neural Network (RNN)
Deep Learning (DL)	Fourier–Bessel series expansion-based empirical wavelet transform (FBSE-EWT)
Deep Convolutional Neural Network (DCNN)	
Artificial Neural Network (ANN)	Gramian Angular Difference Field (GADF)
Fuzzy Logic (FL)	Principal Component Analysis Network (PCANet)
Back Propagation Neural Network (BPNN)	Multiple-Feature-Branch Convolutional
Bayesian Artificial Neural Network Hermite Expansion (BANN-HE)	Bidirectional Recurrent Neural Network (MFB-CBRNN)
the Area Under the Curve (AUC)	Multi-Lead Residual Neural Network (ML-ResNet)
Naïve Bayes (NB)	Automatic U-Net (AU-Net)
Body Surface Potential Maps (BSPM)	Data Augmentation (DA)
Principal Component Analysis (PCA)	Multi-Lead Attention mechanism integrated with DCNN and Bidirectional
Latent Topic Multiple Instance Learning (LTMIL)	Gated Recurrent Unit (MLA-DCNN- BiGRU)
Discrete Cosine Transform (DCT)	Guangdong Cardiovascular Institute (GCI)
K-Nearest Neighbor (KNN)	
Hidden Markov Models (HMMs)	
Gaussian Mixture Models (GMMs)	
Probabilistic Neural Network (PNN)	
Multilayer Perceptron (MLP)	
Improved Bat Algorithm (IBA)	
Neural Network (NN)	
Radial Basis Function (RBF)	
Discrete Wavelet Transform (DWT)	
Analysis of Variance (ANOVA)	
Empirical Mode Decomposition (EMD)	
Flexible Analytical Wavelet Transform (FAWT)	
Least-Squares Support Vector Machine (LS-SVM)	
Bagging Trees (BTs)	

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2. A systematic literature review for MID diagnosis

In this paper, a Systematic Literature Review (SLR) process is conducted for MID diagnosis based on the published papers between 2000 to 2021 from the Google Scholar search engine. Most papers are extracted from IEEE, Elsevier, and Springer databases. We used the Keywords to find papers such as myocardial infarction disease diagnosis, heart disease diagnosis, artificial intelligence techniques, machine learning (ML), and deep learning (DL). Forty-one papers were checked, of which 25 papers were run for ML methods, and 16 papers were performed for DL methods. The SLR process of MID diagnosis is shown in Figure 6.
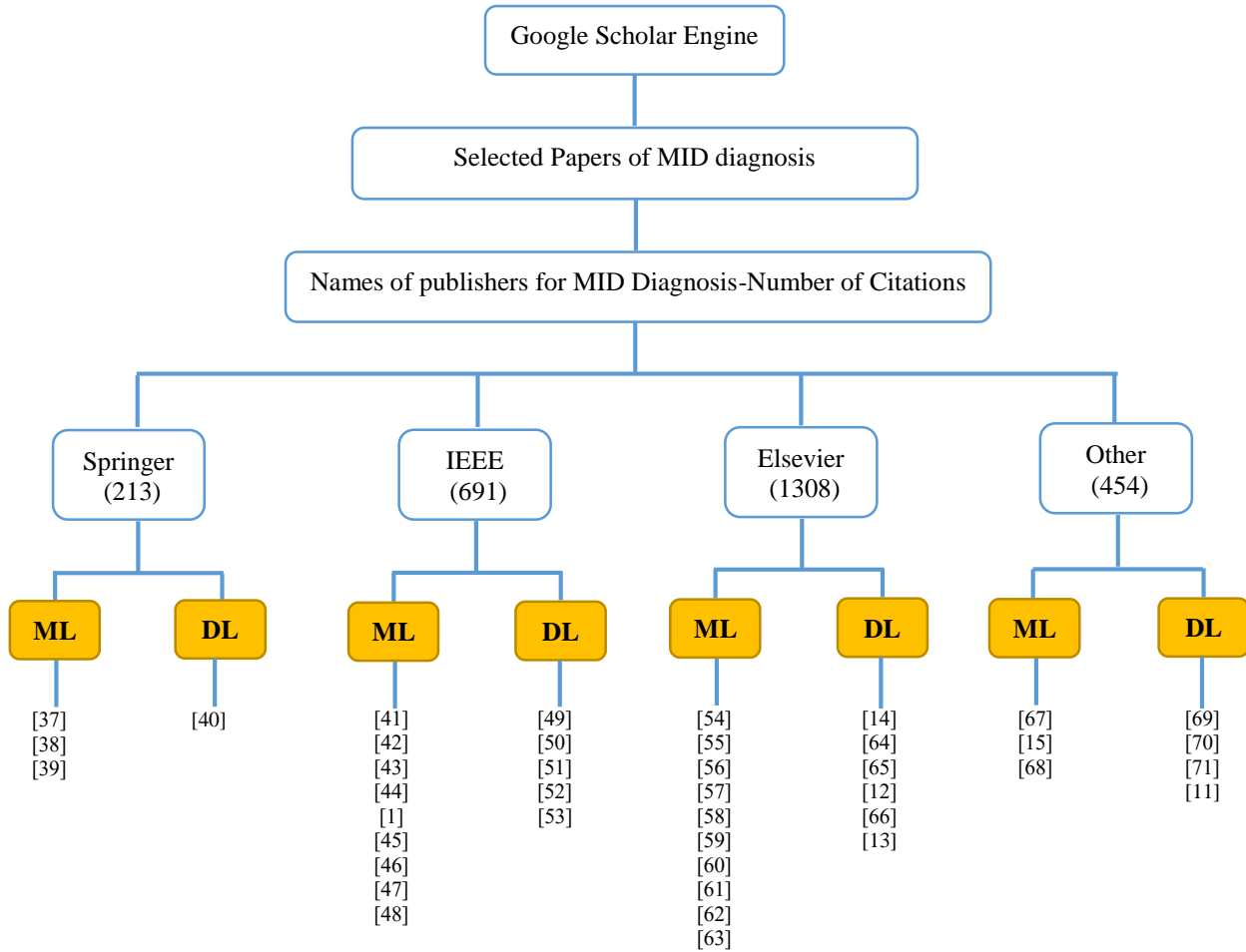

Figure 6. The SLR process of MID diagnosis.

Based on Figure 6, the performed studies for MID diagnosis have been described in Sections 2.1, 2.2, considering ML-based, and DL-based methods.

2.1. ML-based methods

The models have been trained with the part of the data to solve particular problems in machine learning. These models use probabilistic, statistical, and optimization techniques to learn from past experiences and recognize suitable patterns from varous datasets. In these models, the dataset is divided into training, testing, and validation categories. When a model is trained for classification problems, it exploits patterns in the training dataset to represent features to the target, allowing it to foresee according to new data. The training and validation sub-data are performed to renew the model on the interconnection between features and classes. In contrast, the test sub-data is performed to evaluate the model's performance in getting forecasts on the unobserved datasets. Classical machine learning models such as Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Naive Bayes (NB), K-Nearest Neighbor (KNN), and Regression are used for disease classification. As the continues of enhancement of these classifiers, the

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developed model, namely ANN, was made, which is derived from human biological neurons [13]. Hence, the studies that have been conducted based on the machine learning methods for diagnosing MID are as followed.

Readdy et al. [41] have acquired an accuracy of 79% and a specificity of 97% for MID diagnosis using 15 features of the V2- V4 chest lead QRS measurement and with the ANN-feedforward classification.

Hedén et al. [67] have used 1120 ECGs of MID patients, and 10,452 normal ECGs applying the ANN classification method and achieved a sensitivity of 95% and a specificity of 86.30%.

Lu et al. [42] designed a neuro-fuzzy method for the classification and diagnosis of MID on 12-lead ECG signals. Their proposed method includes Fuzzy Logic (FL) theory and Back Propagation Neural Network (BPNN). As a result, the proposed FL-BPNN method obtained an accuracy of 89.4% for MID and an accuracy of 95.0% for normal subjects.

Haraldsson et al. [54] have developed a 12-lead ECG-based MID diagnosis method using Bayesian Artificial Neural Network trained by Hermite Expansion coefficients called BANN-HE at the emergency department of the University Hospital in Lund, Sweden. Based on the BANN-HE method, the Area Under the Curve (AUC) is 83.4% on 2238 ECG signals. Moreover, an accuracy was obtained 94.0% for the MID subjects and 93.3% for subjects without MID through the original ANN.

In [43], the diagnosis of MID was studied by Zheng et al., using SVM, NB, and RF, on the 192 lead Body Surface Potential Maps (BSPM). The results demonstrate that the above methods regarding accuracy were obtained 82.8%, 81.9%, and 84.5%, respectively.

In a study by Arif et al. [44], a BPNN method was proposed to diagnose and localization of MID on the PTB database. They achieved the classification accuracy of 93.7% using the BPNN method with the extracted features based on the Principal Component Analysis (PCA) technique.

Sun et al. [1] have presented a Latent Topic Multiple Instance Learning (LTMIL) method for MID diagnosis with 12 ECG leads. They use Discrete Cosine Transform (DCT) bandpass filters for signal processing and five-order polynomial fitting to determine 74-dimensional feature spaces. They also have been developed the particle swarm optimizer for variable weighting, and it has been modeled as a Gaussian distribution, which means the heart rate distribution. The classification was done with SVM, NN, KNN, RF, and ensemble learning achieve the high accuracy of 90% by KNN ensemble combined with LTMIL.

A study has been done by Arif et al. [37] for the diagnosis and localization of MID using the KNN method on the 20,160 ECG beats from the PTB database. In the experimental phase, they have used 10080 heartbeats for non-pruning training and 711 beats for pruning training performing the proposed method on half of the randomly selected pulses for MID automatic diagnosis. In the following, 36 dimensions of the feature vector were determined using the dual wavelet transform method on the ECG signals. Finally, dividing MID rates into 11 classes (10 classes for infarct site and 1 class for normal subjects, they have reached the sensitivity and specificity above 90% and the overall classification accuracy of 98.8%. The overall classification achieved an accuracy of 98.3% through the proposed method by pruning the training dataset.

In [55], Chang et al. have been studied MID diagnosis based on four chest lead (V1, V2, V3, and V4) with Hidden Markov Models (HMMs), Gaussian Mixture Models (GMMs), SVM, and Viterbi methods from the Taoyuan Armed Forces General Hospital located in Taiwan. In their study, 582 MID and 547 normal heartbeats were tested so that the results demonstrate that the combined HMMs and GMMs method has a maximum accuracy of 82.50% for the diagnosis of MID.

Safdarian et al. [15] investigated classification methods such as Probabilistic Neural Network (PNN), KNN, Multilayer Perceptron (MLP), and NB for the diagnosis and localization of MID. As a result, they achieved 94.74% accuracy for MID diagnosis using the NB classifier and the accuracy of 76.67% for MID localization using the PNN method.

Kora et al. [38] have improved a Bat Algorithm called (IBA) to extract the main features of each heartbeat from the PTB database, including 148 MID subjects and 52 normal subjects. The best features are extracted through the proposed algorithm and then applied to the backpropagation Levenberg–Marquardt Neural Network (LMNN) classifier input. As a result, the performance of the classifier is improved with the help of optimized features, so that the IBA method combined with LMNN regarding the accuracy of 98.9% performs better than the classification methods such as SVM, LMNN, scalar conjugate gradient neural network, and KNN for MID diagnosis.

Sharma et al. [45] have implemented multiscale energy and eigenspace approach for MID diagnosis. According to this approach, the wavelet decomposition of multi-lead ECG signals is applied to clinical components in different subgroups. Moreover, a frame with four beats from each ECG lead is used to diagnose a heart attack. In addition, out of 1074 subjects of MID and 1074 subjects of normal to determine the characteristics of 72-dimensional vectors of 12-lead ECG signals, multilayer ECG frames are controlled. The ECG classification performed with applying SVM with Radial Basis Function (RBF) kernel, linear SVM, and KNN classifiers so that the best accuracy has been achieved 96.0% for MID diagnosis.

Acharya et al. [56] suggested a KNN classifier to classify normal and ml ECG signals, including 611,405 signals (125652 normal and 485.753MI) and Subjects (148 MID of 10 types and 52 normal) on the ECG signals from the PTB database. Each signal is subjected to four levels of Discrete Wavelet Transform (DWT) decomposition using Daubechies six wavelet basis function. Then 12 types of nonlinear properties are extracted from DWT coefficients. Finally, essential features are ranked based on their t-values and F-values doing t-test and Analysis of Variance (ANOVA) techniques. The ANOVA test was used to rank more than two characteristics of the class, namely normal and ten types of MID. The results of the proposed method show that the classification accuracy of the normal and MI classes is 98.80% based on 47 characteristics from lead 11 (V5). In addition, they achieved an accuracy of 98.74% for diagnosis and classification of 11 classes (10 types of MI and normal) based on 25 characteristics from 9lead (v3). Meanwhile, they obtained an accuracy of 99.97% for localization based on nine lead (v3).

Acharya et al. [57] have compared three methods such as DWT, Empirical Mode Decomposition (EMD), and DCT to diagnose of CAD and MID. In their study, ECG signals are subjected to DCT, DWT, and EMD to obtain the corresponding coefficients. These coefficients are reduced using the Locality Preserving Projection (LPP) method. Then, the LPP features are ranked with the help of the F-value. Finally, highly ranked coefficients are placed in the KNN classification to achieve the best classification performance. The highest accuracy rate of 98.5% is obtained through the DCT Coefficients combined with KNN on the ranked seven features.

Kumar et al. [68] have used a sample entropy in Flexible Analytical Wavelet Transform (FAWT) structure to diagnose MID on the ECG heartbeat signals. Firstly, the ECG signals are segmented into pulses. Then, FAWT is developed for each ECG beat to decompose them into sub-band signals. Sample entropy is determined from these sub-band signals, and it is given to different classifiers. Based on the FAWT combined with the least-squares support vector machine (LS-SVM) classifier, the highest classification accuracy of 99.31% was obtained compared to the RF, J48 decision tree, and BPNN classification methods.

Khatun and Morshed [46] studied the Bagging Trees (BTs) classification method to diagnose MID on the single-lead ECG data. The proposed method identifies the points P, Q, R, S, and T on the ECG signals automatically, so that were extracted 33 features, including 15 types of interval and 18 types of amplitude. Using the BTs method, MID is diagnosed with an accuracy of 99.7% based on a single lead ECG data (Lead V4).

Acharya et al. [58] have introduced the KNN classifier to classify MID on the lead II ECG signals from the PTB database. The essential features were selected using the improved binary particle swarm optimization method of the ECG signals. The selected features are graded utilizing ANOVA and relief methods. High-ranking features were applied to the DT and KNN methods. They gained 99.55% accuracy through the KNN method with contourlet transform based on the 20 selected features on the ECG signals. They also obtained 99.01% accuracy using shearlet transform with the same number of features.

Dohare et al. [59] tried to use the SVM with PCA reduction technique to diagnose MID based on 12-lead ECG signals so that each lead ECG is analyzed with the aid of composite lead. Meanwhile, the PCA method is utilized for reducing computational complexity and feature size. They achieved 98.33% accuracy using the SVM method on primary features 220, whereas they obtained 96.66% accuracy through the SVM with PCA.

Diker et al. [47] developed the SVM method combined with a Genetic Algorithm (GA) on the ECG signals from the PTB database to diagnose MID. In their study, identification of ECG signals is made using morphological features, time-domain, and DWT to diagnose MID subjects from normal. In total, 23 features were extracted. The results dedicate that nine features are identified by GA. In addition, the dimensions of the features were reduced from 23 to nine, and an accuracy of 87.8% is obtained on the nine selected features using SVM with GA, whereas an accuracy of 86.44 is achieved using SVM with 23 features.

Han and Shi [60] discussed SVM-RBF, SVM with polynomial, linear SVM, BTs, and BPNN methods for MID diagnosis on 148 subjects, 368 records, 28213 MID beats, and 5373 normal beats from the PTB database. They developed a combination of global energy entropy features based on Maximal Overlap Discrete Wavelet Packet Transform (MODWP) and local morphological features to extract features on the ECG signals. Then they suggested PCA, linear discriminant analysis, and locality preserving projection methods to reduce the number of features after the fusion of multi-lead ECG signals. The results dedicate that SVM-RBF with the 10 Fold-Cross Validation (FCV) technique has the best accuracy of 99.81% based on 18 features for the intra-patient pattern, as well as with the same method for the inter-patient pattern, 92.69% accuracy was gained based on 22 features.

Zhang et al. [48] presented staked Sparse Autoencoder (SAE) with Tree Bagger (TB) for diagnosing and locating MID from single-lead ECG signals from the PTB database. The feature extraction network in SAE-based diagnosis uses a layer-wise training strategy to avoid the vanishing gradient problem. It learns the optimal feature expression from the heartbeat without input tag. Hence, this method extracts deep, distinctive features from single-lead ECG signals. The TB classifier is designed to understand MID diagnosis combining the results of several decision trees and optimization of features. The experiments show that the accuracy of 99.90%, the sensitivity of 99.98%, and the specificity of 99.52% are obtained using the SAE combined with the TB method.

Zeng et al. [61] proposed the neural network method with RBF for early diagnosis of MID based on 12-lead and Frank XYZ leads ECG signal segments from the PTB database. Tunable quality factor wavelet transform, variational mode decomposition, and phase space reconstruction methods are assigned as nonlinear feature extraction methods to form cardiac vectors based on the synthesis of 12-lead ECG signals, and Frank XYZ leads. Ultimately, these feature vectors are forwarded into dynamical estimators, which are comprising RBF-neural network for the modeling, diagnosis, and classification of MID and healthy subjects. The proposed method has the best performance regarding the accuracy of 97.98% using the 10-FCV technique.

Kayikcioglu et al. [62] developed SVM and KNN classification algorithms for ECG classification. Besides, the ensemble classification algorithms such as boosted trees, and BTs, Subspace KNN are used. Three databases are utilized such as MIT-BIH Arrhythmia database, the European ST-T database, and the Long-Term ST database. Moreover, these databases classified into four classes as Healthy, Arrhythmia, ST Depression, and ST Elevation. In their study, quadratic time-frequency distributions including smoothed Wigner-Ville, the Choi-Williams, the Bessel, and the Born-Jordan were applied on 5-lead ECG signals to extract the features. The results demonstrate that using the weighted KNN algorithm, a high accuracy of 94.23% is obtained based on the extracted features by the Choi-Williams time distribution.

Liu et al. [63] proposed a single-beat MID diagnosis system using the Dual-Q Tunable Q-factor Wavelet Transformation (Dual-Q TQWT) denoising algorithm of ECG. The results were demonstrated that the proposed system with Dual-Q TQWT and wavelet packet tensor decomposition has better performance than DWT, EMD denoising methods. Also, a TB classifier was performed for the classification of MID records from normal records. Finally, they achieved 99.98% accuracy in beat level and 97.46% accuracy in record level for MID diagnosis using Dual-Q TQWT + DWPT + MPCA + TB system.

In another study, Lin et al. [39] designed a KNN classification model to diagnose MID from the PTB database. They utilized the Maximal Overlap Discrete Wavelet Packet Transform (MODWP) to decompose the ECG signal, extracted the variance, interquartile range, Pearson correlation coefficient, Hoeffding's D correlation coefficient, and shannon entropy of the wavelet coefficients was performed. By using the proposed model, the accuracy of MID diagnosis was obtained 99.57%.

2.2. DL-based methods

Deep learning methods, unlike machine learning methods, have more hidden layers so that the number of the middle layers is about hundreds or more layers. DL methods can be performed by extensive data, unlike ML methods which conduct with a smaller dataset.

Also, in DL methods, the input dataset passing each layer is transformed at each layer in sequence, until it is significantly different from its original state at the last layer. The transformation of the dataset is prompted through the reformed linear activation functions such as Relu, Sigmoid, softmax, and Hyperbolic Tangent. For example, Sigmoid function activation for binary classification and Softmax function for multi-class classification is used in the last network layer [13]. The DL-based models such as Deep Convolutional Neural Network (DCNN), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and autoencoder network used for disease classification. Among these models, DCNN has better performance for processing and classifying signals compared to the ML methods [72]. Moreover, feature extraction and feature selection processes using DL methods are performed automatically, whereas these processes need to be handcrafted in standard ML methods. Due to the mentioned descriptions for DL-based methods and ML-based methods, in this section, the related works to DL-based methods for MID diagnosis are review in detail.

Acharya et al. [14] implemented the 11 layer DCNN method for MID diagnosis on 10,546 normal signals and 40,182 MID signals with and without noise, and Lead 2 ECG. As a result, the accuracy rates of MID diagnosis using the proposed DCNN method in terms of noise and without noise are obtained at 93.53% and 95.22%, respectively. However, their proposed method has been performed considering two ECG signals with noise and without noise, compared to the KNN classifier in [56], that was made based on 12-lead ECG signals, which had a diagnostic accuracy of 98.80%.

Reasat and Shahnaz [49] devised a DCNN architecture that gives raw ECG signals from leads II and III, and AVF so that inferior myocardial infarction and normal signals are separated from each other. The proposed DCNN network is implemented based on a person-centered approach. According to this approach, DCNN was tested on one patient and was trained on the other patients. The diagnosis accuracy of the proposed method has increased compared to the Stationary Wavelet Transform (SWT) with KNN and the SWT with SVM [73] methods so that the best accuracy rate is gained 84.54% through DCNN than the above methods.

Lui and Chow [64] proposed a DCNN method combined with Recurrent Neural Network (RNN) on ECG (Lead I) records to diagnose MID. They have applied a family of RNN known as long short-term memory stacking decoding. The proposed method was compared with a pure DCNN and MLP classifier with hand-crafted features. The DCNN-

RNN method has better performance than pure DCNN and MLP methods in terms of sensitivity with 92.4%, specificity of 97.7%, the positive predictive value of 97.2%, and F1 score of 94.6% for the MID diagnosis.

Gupta et al. [40] have developed a deep learning model under the name of the modified ConvNetQuake neural network to identify ECG changes that may correctly classify cardiac conditions. The proposed ConvNetQuake model has been modified to obtain raw ECG records from both Leads (V6) and (VZ) simultaneously. Also, their proposed model is different from related works because their ECG records were entered into their neural network model that does not require handcrafted feature extraction or preprocessing. As a result, an accuracy of 99.43% was obtained using the developed DCNNQuake model, which demonstrates the level of cardiovascular surface performance for the diagnosis of MID after feeding only 10 seconds of raw ECG records to the proposed model.

Baloglu et al. [65] have presented a DCNN model with an end-to-end structure on the 12-Lead ECG signals for MID diagnosis. Their trained DCNN model had an impressive accuracy of 99.78% on Lead (V4) for MID diagnosis.

Tripathy et al. [50] designed a deep learning model with a least-square support-vector machine called DL-LSSVM, which is developed by the hidden layers of sparse auto-encoders. They have used the LSSVM method to diagnose MID based on the feature vector of 12-lead ECG signals. Meanwhile, they proposed a new approach named Fourier–Bessel Series Expansion-based Empirical Wavelet Transform (FBSE-EWT) for the time-scale decomposition and the diagnosis of MID pathology of signals. The results dedicate that the combination of a DL-LSSVM model with FBSE-EWT-based entropy features has the best accuracy of 99.74% for MID diagnosis. In addition, the accuracy rate of the hybrid method is increased by higher than 3% compared to the wavelet-based features for the diagnosis of MID.

In a study by Zhang et al. [51], three methods such as Gramian Angular Difference Field (GADF), Principal Component Analysis Network (PCANet i.e., the lightweight DCNN-like model), and Linear SVM were performed to extract crucial features from each image, and to diagnose MID automatically based on Lead II from the PTB database. Based on the Class-oriented scheme, achieved an accuracy of 99.49% (beat type: noise) and 98.44% (beat type: no noise) using GADF + PCANet + Linear SVM with 5-FCV, and the MID diagnosis accuracy reached 93.17% for the Patient-oriented scheme.

Feng et al. [69] proposed a multi-channel classification algorithm, which is the combination of a 16-layer DCNN and the LSTM net, to diagnose ECG signals of MID. Firstly, the proposed algorithm processes the raw signals to extract the various segments of the heartbeat. Then it is trained by the multi-channel DCNN and LSTM net to learn the obtained features automatically and perfect the ECG classification of MID. Using the 16-layer DCNN-LSTM method was gained a high accuracy rate of 95.4% without handcrafted features.

Liu et al. [52] suggested a new hybrid network named Multiple-Feature-Branch Convolutional Bidirectional Recurrent Neural Network (MFB-CBRNN) to diagnose MID based on 12 leads. In this proposed model, DCNN-based and RNN-based structures are effectively combined. In addition, a bilinear long-short term memory network is applied to more summarize the features from the 12-lead ECG records. The used MFB-CBRN method had an accuracy of 99.90% for the class-oriented scheme and obtained an accuracy of 93.08% for the subject-oriented scheme on 12-lead ECG records.

Strodthoff and Strodthoff [70] used an ensemble method of Fully-Connected DCNN called DCNN-FC to diagnose the MID based on the PTB database considering the most proper clinical subjects of 12 leads. Based on the DCNN-FC method, the sensitivity of 93.3% and specificity of 89.7% obtained using the 10-FCV technique with a sampling of patients.

Han and Shi [12] developed a Multi-Lead Residual Neural Network (ML-ResNet) model with three residual blocks and feature fusion for MID diagnosis based on 12-lead ECG signals from the PTB database. The results demonstrate that the ML-ResNet model gains an accuracy of 95.49% for the inter-patient scheme. In contrast, the accuracy is obtained 99.92% with the same method for the intra-patient scheme.

Kim et al. [66] utilized the DCNN models such as U-Net, including Semi-automatic u-Net, Automatic U-Net (AU-Net), and automated encoder-decoder u-Net with Monte Carlo dropout sampling to estimate uncertainty in u-Net model fully automatic based on the cardiac perfusion image dataset for myocardial segmentation. Their results regarding average Dice similarity criterion using the proposed AU-Net method based on uncertainty estimation of 0.806 (average ± standard deviation: ± 0.096) performs better than the semi-automatic and automatic u-Net models in terms of the same criterion with values of 0.808 (average ± standard deviation: ± 0.084) and 0.729 (average ± standard deviation: 0.147).

Natesan et al. [53] developed DCNN with Data Augmentation (DA), DCNN without DA, and DCNN with noise to classify MID based on multi-lead signals from the PTB database. The results dedicate that the DCNN method with DA has more accuracy of 94.98% than DCNN without DA, and DCNN with the noise of 90.34% and 90.93%, respectively.

Fu et al. [71] designed a new MID diagnosis mechanism called a Multi-Lead Attention mechanism integrated with DCNN and Bidirectional Gated Recurrent Unit (MLA-DCNN- BiGRU) framework on 12-lead ECG signals from the PTB database. To enhance the performance of MID diagnosis through the MLA mechanism, weights are automatically

gained and assigned due to the contribution of each lead for different leads. The two-dimensional DCNN module uses the related properties among leads. Also, Discriminative Spatial Features (DSFs) are extracted by the DCNN module. Meanwhile, the BiGRU module extracts Essential Temporal Features (ETFs) within each lead. DSFs and ETFs are combined for classification. According to the intra-patient scheme and inter-patient scheme, using the proposed MLA-DCNN-BiGRU mechanism, an accuracy of MID diagnosis obtained 99.93% for the Intra-Patient scheme, and an accuracy of diagnosis of MID was achieved 96.5% for the inter-patient scheme.

In another study, Tadesse et al. [11] researched an end-to-end DL approach to diagnose MID and normal subjects. In addition, the occurrence-time is expressed as acute, recent, and old classes of MID subjects by deep multi-lead ECG fusion through 12-lead ECG signals in Guangdong Cardiovascular Institute (GCI). Based on the proposed DL approach, three diagnosis modeling techniques are extended, such as spectral, longitudinal, and spectral-longitudinal. The Dens-LSTM method was utilized for classifying the data. Moreover, they used transfer learning architectures, including GoogLeNet and MnasNet to feature encoding, decreasing computational overhead and complexity, and reduced net training loss rate. The obtained results demonstrate that between three modeling techniques, the spectral-longitudinal is the best technique regarding the AUC criterion with 85.2% using MnasNet features from the GCI database. In contrast, the accuracy of 73.2% using the Longitudinal technique is better than other techniques. Moreover, the Spectral-Longitudinal method combined with the Dens-LSTM classifier has the best AUC of 94% compared to the other techniques from the PTB Database.

Diagnosis of MID, CAD, CHF, and Normal was presented by Jahmunah et al. [13] using DCNN and Gabor-Filter DCNN models on Lead II ECG signals. The Gabor filter was used to classify MID and normal subjects so that in the DCNN model, eight Gabor filters were replaced with the convolution layer to reduce computational complexity. According to the Gabor-Filter DCNN model, for four classes MID, CAD, CHF, and normal, an average accuracy rate was obtained 99.55%, and accuracy of 98.74% was gained using DCNN. In addition, the accuracy was obtained 99.68% using the Gabor-DCNN model of MID diagnosis, and the accuracy was achieved 99.95% through the DCNN model.

3. Results and Discussion

In this section, firstly, the results for ML-based and DL-based methods are presented in Tables 2 and 3, respectively. Then the trend of conducted researches during different years for MID diagnosis is discussed in detail.

Table 2. MID diagnosis using ML-based methods.

No.	References	No. Citations-Publishers	Methods	No. K-FCV	Dataset	Code Environment	ACC (%)
1	Readdy et al., [41]	39-IEEE	ANN	NC	Leads: v2-v4 Subjects: 272 MID, 479 Normal	Custom program developed at Glasgow Royal Infinnary and Siemens Elema AB (Solna, Sweden)	79
2	Hedén et al., [67]	195- Other	ANN	8-FCV	Leads: 12 leads Subjects: 1120 MID, 10452 Normal from PTB database	JETNET 3.0 package	N/A
3	Lu et al., [42]	70- IEEE	FL-BPNN	NC	Leads: Lead 12 subjects: 20 normal, 104 MID	NC	89.4 for MID, 95.0 for Normal
4	Haraldsson et al., [54]	115-Elsevier	ANN	3-FCV	Leads: 12 leads subjects: 2238 ECGs; 699 men and 420 women for MID group, 578 men and 541 women for Normal group	The bootstrap: A tutorial. Chemometr Intell Lab System	94 for MID, 93.3 for Normal
5	Zheng et al., [43]	17-IEEE	Random Forest	10-FCV	Leads: 192 lead BSPM Subjects: 116; 57 MID, 59 Normal from PTB database	Weka package	84.5

6	Arif et al. [44]	47-IEEE	BPNN+ PCA	NC	Leads:12 leads Subject:148 MID and 52 Normal from PTB database	Matlab	93.7
7	Sun et al. [1]	169-IEEE	KNN ensemble+ LTMIL	10-FCV	Leads:12 leads Subject: 369 MID, 79 Normal from PTB database	Matlab	90
8	Arif et al. [37]	148-Springer	KNN	10-FCV	Leads: 12 leads Subjects: 10 types of MID, 1 Normal from PTB database	NC	98.3%
9	Chang et al. [55]	102- Elsevier	HMMs + GMMs	NC	Leads: lead (V1-V4) Subjects: 1129 samples of heartbeats; 582 MID, 547 Normal	Matlab	85.71
10	Safdarian et al., [15]	75-Other	NB	NC	Leads: 12 leads Subjects: 290; 52 Normal 148 MID from PTB database	MATLAB	94.74
11	Kora et al., [38]	60-Springer	IBA+LMNN	NC	Leads: lead 3 Subjects: 52 Normal 148 MID from PTB database	Matlab	98.9
12	Sharma et al., [45]	189-IEEE	SVM-RBF	10-FCV	Leads: 12 leads Subject: 200, 148 MID, 52 Normal from PTB database	Matlab	96.0
13	Acharya et al., [56]	128-Elsevier	DWT Coefficients+KNN	10-FCV	Leads: 12 leads Subject: 52 normal, 148 MID from PTB database	NC	98.74
14	Acharya et al., [57]	143- Elsevier	DCT Coefficients+KNN	10-FCV	Leads: lead 2 Subject: 148 MID, 52 Normal from PTB database	NC	98.5
15	Kumar et al., [68]	83-Other	LS-SVM	10-FCV	Leads: lead 2 subjects: 52 Normal and 148 MID from PTB database	Matlab	99.31
16	Khatun and Morshed, [46]	9-IEEE	BTs	10-FCV	Leads: 12 leads subjects: 79 normal, 346 MID from PTB database	Matlab	99.7
17	Acharya et al., [58]	66- Elsevier	CWT-based controlet+ KNN	10-FCV	Leads: 12 leads Subjects: 148 MID, 52 Normal from PTB database	NC	99.55
18	Dohare et al., [59]	62- Elsevier	SVM+PCA	10-FCV	Leads: 12 leads subjects: 290, 60 MID, 60 Normal from PTB database	Matlab	96.66
19	Diker et al., [47]	21-IEEE	GA+SVM	10-FCV	Leads: 12 leads subjects: 290; 148 MID, 52 Normal from PTB database	NC	87.8
20	Han and Shi, [60]	27- Elsevier	SVM-RBF	10-FCV	Leads: 12 leads subjects: 148 MID, 52 Normal from PTB database	Matlab	99.81
21	Zhang et al. [48]	13-IEEE	SAE+TB	10-FCV	Leads: lead 2 subjects: 368 records from 148 MID, 80 records from 52 Normal from PTB database	NC	99.90

22	Zeng et al., [61]	4- Elsevier	RBF-neural network	10-FCV	Leads: 12 leads Subjects: 290, 148 MID, 52 Normal from PTB database	Matlab	97.98
23	Kayikcioglu et al., [62]	6-Elsevier	Weighted KNN	10-FCV	leads: lead (V1-V5) Subjects: European ST-T (17 persons, 70 ECG recordings, 70 men), MIT-BIH Arrhythmia (46 different patients) and Long-Term ST (17 persons, 70 ECG recordings, 70 men)	NC	94.23
24	**Liu et al. [63]**	**11- Elsevier**	**Dual-Q TQWT + DWPT + MPCA + TB**	**10-FCV**	**Leads: 12 leads and 3 Frank leads (VX, VY, VZ) Subjects: 290 subjects , 209 men, 78 Normal, 328 MID from PTB database**	**Matlab**	**99.98 in beat level, 97.46 in record level**
25	Lin et al., [39]	1-Springer	KNN	10-FCV	Leads: 12 Leads subjects: 148 MID and 52 Normal from PTB database	Matlab	99.57

NC: not considered

Based on Table 2, between the proposed methods, Dual-Q TQWT + DWPT + MPCA + TB is the best method regarding accuracy rates of 99.98% in beat level and 97.46% in record level for MID diagnosis from the PTB database.

Table 3. MID diagnosis using DL-based methods.

No.	References	No. Citations-Publishers	Methods	No. K-FCV	Dataset	Code Environment	ACC(%)
1	Acharya et al., [14]	448-Elsevier	DCNN	10-FCV	Leads: lead 2 subjects: 200 subjects; 148 MID, 52 Normal from PTB database	NC	93.53 with noise, 95.22 without noise
2	Reasat and Shahnaz, [49]	39-IEEE	DCNN	NC	Leads: Lead 2, 3 and AVF Subjects: 148 MID, 52 Normal from PTB database	Python	84.54
3	Lui and Chow, [64]	37- Elsevier	DCNN-RNN	10-FCV	Leads: lead 1 Subjects: 290 subjects with 209 males and 81 women; 148 MID and 52 Normal from PTB database	NC	NC
4	Gupta et al., [40]	4-Springer	DCNNQuak	100-FCV	Leads: 12 leads along with 3 Frank leads Subjects: 290; 52 Normal, 148 MID from PTB database	Python	99.43 for record-wise split, 97.83 for patient-wise split
5	Baloglu et al., [65]	124-Elsevier	DCNN	NC	Leads: 12 leads Subjects: 52 Normal, 148 MID from PTB database	Python	99.78

6	Tripathy et al., [50]	46-IEEE	DL-LSSVM	5-FCV	Leads: 12 leads Subjects: 290, 148 MID, 52 Normal from PTB database	NC	99.74
7	Zhang et al., [51]	6-IEEE	GADF+PCANet+Linear SVM	5-FCV	Leads: lead 2 Subjects: 290, 52 Normal, 148 MID from PTB database	Matlab	93.17 for patient-oriented scheme, 99.49 for class-oriented scheme with noise, 98.44 for class-oriented scheme with noise
8	Feng et al., [69]	18-Other	16-layer DCNN+LSTM	10-FCV	Leads: lead 1 Subjects: 148 MID, 52 Normal from PTB database	Python	95.4
9	Liu et al. [52]	23-IEEE	MFB-CBRNN	5-FCV	Leads: 12 leads Subjects: 148 MID, 52 Normal from PTB database	Python	99.9 for class-oriented scheme, 93.08 for subject-oriented scheme
10	Strodthoff and Strodthoff, [70]	76-Other	DCNN-FC	10-FCV	Leads:12 leads Subjects: 127 MID, 52 Normal	Python	NC
11	Han and Shi, [12]	26-Elsevier	ML-ResNet	5-FCV	Leads: 12 leads Subjects: 52 Normal, 113 MID from PTB database	Python	95.49 for inter-patient scheme, 99.92 for intra-patient scheme
12	Kim et al., [66]	8- Elsevier	AU-Net	NC	Leads: NC Subjects: 35 subjects; 14 coronary artery disease, 8 hypertrophic cardiomyopathy, and 13 Normal	NC	NC
13	Natesan et al., [53]	3-IEEE	DCNN+DA	NC	Leads: 12 leads Subjects: 148 MID, 52 Normal from PTB database	NC	94.98
14	Fu et al., [71]	7-Other	MLA-DCNN-BiGRU	5-FCV	Leads: 12 leads Subjects: 148 MID, 52 Normal from PTB database	Python	99.93 for intra-patient scheme, 96.5 for inter-patient scheme
15	Tadesse et al., [11]	0-Other	Longitudinal+MnansNet	10-FCV	Leads: 12 leads Subjects: 148 MID, 52 Normal from PTB database; 11853 MID, 5528 Normal from GCI database	NC	73.2 based on GCI database
16	Jahmunah et al. [13]	0-Elsevier	DCNN	10-FCV	Leads: Lead II Subjects: 148 MID, 52 Normal from PTB database	Python	99.95

NC: not considered

According to table 3, the DCNN method has the highest accuracy of 99.95 compared to other methods for MID diagnosis from the PTB database.

As resulted from Tables 2 and 3, the deep learning methods have been more used in recent years, so that no paper in 2021 was run by machine learning methods. Moreover, the number of citations for the published papers in the Elsevier database is higher than the number of the published papers in other databases. The journal of Information Science has the most citations of 449 for paper [14]. Moreover, the conducted researches process during different years is depicted in Figure 4.
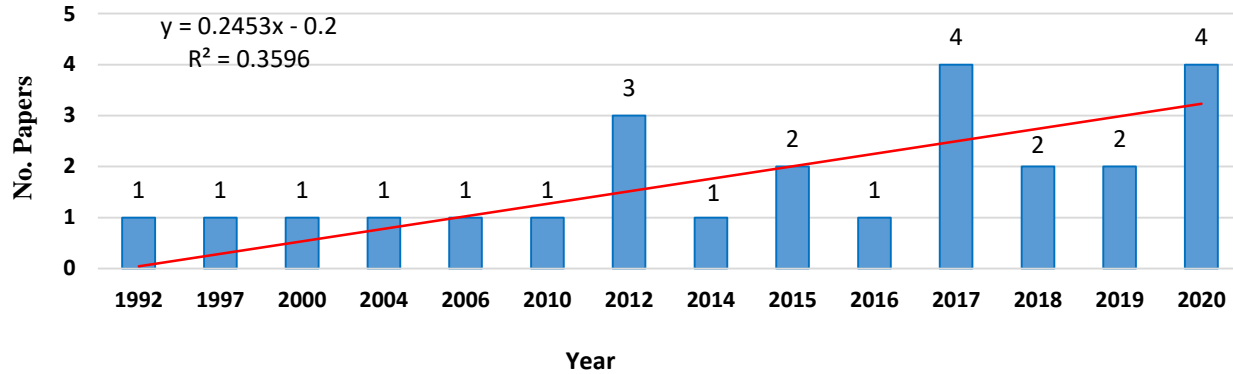

Figure 6. The number of conducted papers for MID diagnosis using ML-based methods between 1992 and 2020.
Figure 6 demonstrates the annual distribution of 25 papers together with a linear trend line. The large Ascending gradient of the trend line shows more published papers in recent years. Furthermore, only one paper was published from 1992 to 2010 annually. From 2010 to 2012, 3 papers were published. From 2012 to 2017, there is a trend of relative changes in the number of papers. Then, in 2018 and 2019, there were two papers each year. Finally, in 2020, four papers were published.
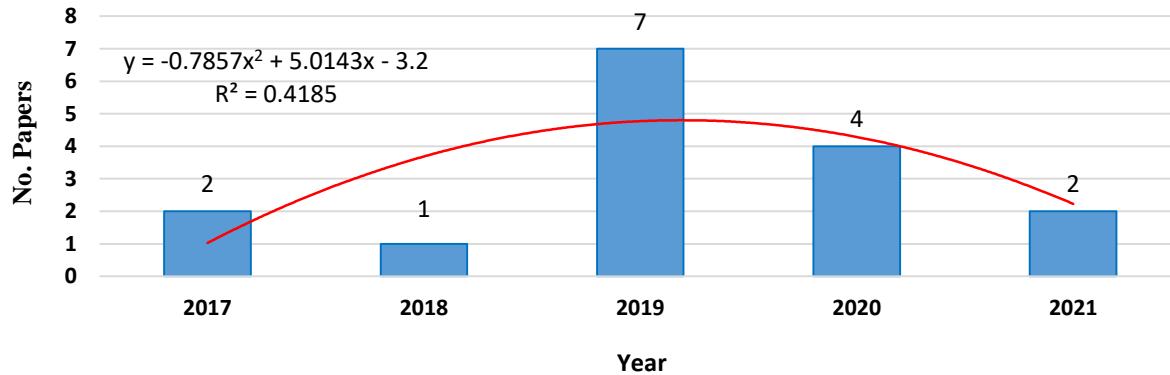

Figure 7. The number of papers for MID diagnosis using DL-based methods between 2017 and 2012.

According to Figure 7, the annual distribution of 16 papers together with a polynomial trend line. Two papers were published in 2017, and in 2018, one paper was conducted. The number of papers had reached seven. Eventually, from 2019 to 2021 had decreased to two papers with a moderate gradient.
In general, we observe an average increase in the number of papers of MID diagnosis using ML and DL methods.

4. Conclusions and Open Research Paths

Myocardial infarction has the highest mortality of cardiovascular diseases. To diagnose MI about its occurrence time is vital to the medical interventions to help CVD patients. Because of the cost and delay of getting blood sample tests from the laboratory, using the electrocardiogram (ECG) signals is another conventional clinical trial currently used to screen MID patients. Nevertheless, using ECG is time-consuming and tends to subjective bias. Hence, Machine Learning (ML) and Deep Learning (DL) methods are used to overcome the above challenges for MID diagnosis automatically. Using the ML methods, feature extraction and selection of ECG signals need to be handcrafted. These operations are performed automatically in Deep Learning (DL) methods. Therefore, we review the methods based on ML and DL that are used to diagnose MID. We collected the papers assigning keywords such as myocardial infarction disease diagnosis, heart disease diagnosis, artificial intelligence techniques, machine learning, and deep learning from

the Google scholar engine. Twenty-five papers are using ML methods, and 16 papers are regarding DL methods. The DCNN methods have resulted in the highest accuracy for MID diagnosis in deep learning. As a result, most researchers have tended to use DL methods in recent years. As open research paths, there are some aspects; one is to improve the diagnosis accuracy for MID using DL methods. Also, enhancing the time of preparing input signals and preprocessing. Furthermore, to automate the input preparation, reducing noises, and conducting output to achieve a fully automated process. Therefore, using the DL methods in portable devices to convey to the patients easily.

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