Machine Learning based Heart Disease Diagnosis using Non-Invasive Methods: A Review

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Abstract. Heart disease is the most dangerous disease among all the non-communicable diseases. Annually 17900 thousand of peoples die due to heart problems. Cardiovascular disease (CVD) is the general term used for most of the heart diseases. There are two types of methods for diagnosing a CVD: (i) Invasive Methods (ii) Non-Invasive Methods. Coronary angiography is an invasive method for diagnosing a CVD which is a costly, painful and complicated process. A variety of Non-Invasive (NI) methods are available for diagnosing a CVD. NI methods generate a lot of data which is mainly of 3 kinds : (i) data based on clinical parameters, lab tests and symptoms (ii)data based on raw heart signals (ECG and PCG) (iii)data based on heart images. Majorly, three different machine learning (ML) frameworks may be developed based on the 3 types of data. First framework is simple and main concern is feature selection and classification. Second and third framework is complicated and requires a lot of techniques (preprocessing, segmentation and feature extraction) prior to classification of heart signals and images respectively. In this paper a comprehensive review is presented that summarizes some recent and prevalent machine learning methodologies in all the frameworks. Most of the papers reviewed in this study are from IEEE Explorer, Science Direct, PubMed, Springer, Hindawi, ACM digital library and MDPI libraries. It is found that Support Vector Machines (SVM) and Artificial Neural Networks (ANN) are superseding in most of the studies in all the frameworks. Deep neural network is comparatively newer machine learning methodology which is giving prominent results in classifying heart sound signals and cardiovascular images. The present study will help to automate diagnosis process of heart disease by providing guidelines and avenues to new researchers in domain of machine learning.

Keywords: Cardiovascular Disease, Machine Learning, Non-Invasive Methods, Classification, Feature Selection, Feature Extraction.

1. Introduction
Communicable diseases like corona and swine flu spread in speedy manner but these diseases usually have low mortality rates as compared to many of the non-communicable diseases including diabetes, heart disease, liver cancer and breast cancer. Machine learning researchers have a great a focus on the medical data mining that includes various diseases covering breast cancer [1], heart disease [2], diabetes[3], parkinson’s disease [4], hepatitis [5], liver disorder [6], lung cancer[7], pancreatic cancer [8], leukemia [9] and brain tumor [10]. Among the said diseases, heart disease is most dangerous and unpredictable. It has highest mortality rate among all non-communicable ailments. In 2015, more than 17.7 million people died due different heart diseases[11]. A recent study says that every year 17.9 million people die because of heart problems all over the world [12]. Taking this fact as a raw statistic, one can guess around 49000 people die every day due to heart problem worldwide which is very big number. Death rates due to heart
disease in underdeveloped and developing nations are more because of costly diagnosis process.

General terms used for the problem of heart are heart attack or heart failure. However majorly, heart ailments are of different type including (i) congenital heart disease (ii) left sided heart failure (iii) right sided heart failure (iv) ischemic heart disease (IHD), (v) myocardial infarction (vi) arrhythmias (vii) systemic and pulmonary hypertensive heart disease (viii) valvular heart disease (ix) infective endocarditis and non-infective vegetation (x) cardiomyopathies and myocardiatis (xi) pericardial disease (xii) pericardiac tumors [13]. Congenital heart disease [14], usually found in new born babies have low mortality rate and its diagnosis is least addressed by machine learning researchers. All other heart problems come under the umbrella term cardiovascular diseases (CVDs). The vast literature of machine learning based diagnosis of CVDs include diagnosis of IHD [15], arrhythmia [16] and valvular heart disease[17]–[19]. Reason behind the rich literature of these diseases is lying in a fact that these heart ailments are more life threatening.

Among all the deaths due to different CVDs, most of the deaths are subjected to coronary artery disease (CAD). CAD happens because of the formation of substance called atherosclerotic plaque that blocks the blood supply to heart which further results in a heart attack, clinically termed as myocardial infarction (MI). Thus, it is required that one should recognize the early formation of atherosclerotic plaque by some clinical measurement and the formation must be avoided with some specified medical treatment. The heart disease diagnosis can be done either ways using (i) invasive methods or (ii) non-invasive methods [20]. Coronary angiography (CA) is an invasive method which is known to be gold standard for the diagnosis of heart disease. However, it is much costly, complex and requires an expertise for its operation. The dangers associated with the invasive method are dissection of artery and arrhythmia. In some cases, it can cause kidney problems and paralysis. In certain circumstances CA can causes even death[20], [21]. Further, continuous imaging and screening is required in CA which results in high operational cost. Association of high cost in diagnosis is again an infeasible solution especially in under developed and developing nations. So even being a gold standard, its acceptability is not universal and the patients from developing nations like India usually avoid it. Auto detection of CVDs is an important application area of the machine learning which ultimately saves many of the lives as most of the heart diseases are recoverable if detected timely. Decision support system which is based the models of machine learning used in diagnosis is usually termed as clinical decision support system(CDSS), will be promoted by this work. CDSS will not only be beneficial to heart patients but it would be a helpful tool for physicians and even for government.

In this paper a comprehensive and exhaustive review is presented from various studies that used the machine learning methodology for diagnosis of heart problems. It has been observed from the literature studied that the data used to train machine learning models are based on non-invasive (NI) modalities. The remaining part of the paper is organized as following: In section 2, a study of exiting literature is carried out in a categorical way based on the type of data. Various sources of data for heart diseases are also discussed in second section. The recent trends in machine learning methodologies in diagnosis of heart diseases have been discussed in section 3. The effectiveness of machine learning models based on the results has been discussed in section 4. Finally we concluded the paper in section 5.

2. Related Work
It has been observed from the existing literature that three different workflows for the machine learning based heart diseases diagnosis are possible. The 3 workflows are stated as (i) Machine Learning (ML) Framework-A (ii) ML Framework-B (iii) ML Framework-C. The categorization is based on the types of data used for ML models.
2.1. Different diagnosis methods for heart disease and machine learning frameworks

Figure 1 shows different diagnosis methods for heart diseases. A variety of NI methods are available for diagnosis of heart disease unlike CA.

![Figure 1. Diagnosis methods for heart diseases](image)

Based upon the datasets generated from the non-invasive (NI) methods shown in figure 1, different kinds of machine learning (ML) frameworks may be developed for the prediction of a heart disease. These frameworks can be categorized as:

**ML Framework-A:** It uses clinical parameters that include demographic data, symptoms and examination, laboratory test and many other physiological parameters. These data are present in relational form. Attributes of the datasets comes under this framework have numeric, categorical or binary domain.

![Figure 2. Machine Learning Framework-A](image)
ML Framework-B: This framework uses heart signals to diagnose heart disease. The heart signals are further divided into two categories (i) electrical signals (ii) sound signals. The dataset considered under this framework uses raw heart signals i.e., either Electrocardiograms (ECG) or Phonocardiograms (PCG). A good example of such dataset is MIT-BIH (for ECG) and 2016 PhysioNet/Computing in Cardiology (CinC) Challenge (for PCG).

![Diagram of Machine Learning Framework-B]

2.2. Datasets used in machine learning for automated heart disease diagnosis

Patient related data for heart disease are available in different forms of electronic health record [23]. The heart data set generally include clinical and physiological parameters. A standard heart data set may include demographic data, symptoms, electrocardiograms (ECG), features of echocardiography and lab examination [24]. UCI is great source of such data [25]–[28]. Perfusion imaging is done prior to CA and also generates a lot of cardiologic image data involving single photon emission computed tomography (SPECT), scintigraphy, positron emission tomography (PET) etc. [22].

![Diagram of Machine Learning Framework-C]

ECG is most important data that is subjected to arrhythmia. Identification of harmful heart beat through ECG classification leads to the detection of a CVD [31]. Generally, heart beat detection involves methods like threshold-based method [32], method based on digital filter and discrete wavelet transform[20]. The most common source of ECG data used in medical data mining is MIT-BIH arrhythmia dataset [16]. Heart
disease diagnosis are performed efficiently using machine learning techniques with heart sound data also[20]. Heart sound data is expressed in Phonocardiograms (PCG). 2016 PhysioNet/Computing in Cardiology (CinC) Challenge is famous repository for PCG data [33]. UCI data set include 8 data sets that are related the heart ailments. Detailed survey datasets related to CVDs is presented by R. Alizadehsani et al. (2019) in a study that includes 68 databases[11]. Sound data segmentation and classification is performed by some recent studies including deep learning [34]–[36]. The data sets available for heart diseases vary in size from 20 samples to 24 thousand samples while feature size varies from 9 to 55 however median size of sample is 350 with 9 numbers of features. The most frequently used data set is Cleveland data set available in UCI machine learning repository with the sample size 303 and features size 13 [11]. Cardiovascular health study (CHS) is big repository of heart data with 5888 samples and large number of attributes, prepared for the prediction heart stroke. Researchers used this dataset different number of samples and features. Khosla et al. (2010) [37] used CHS as a data set of 4988 examples with 796 features after preprocessing in a study while Tay et al. (2014)[38] used it with 5888 instances and 355 features prior to preprocessing. After preprocessing the instances were reduced to 4612 and 272 features in the later study.

3. Machine learning methodologies used in diagnosis of heart diseases

In this section various models and methods that are pertaining to machine learning different frameworks are discussed. The state of art techniques and methodologies are discussed and compared for all ML-frameworks. Before going into the technique specific details, the general definition of machine learning is presented. Machine learning may be broadly categorized into supervised, unsupervised, reinforcement learning and active learning [39]. In medical domain supervised and unsupervised machine learning has a huge literature. The current study focuses on classification which is a supervised machine learning approach. Classification is a process of building a or by learning a mapping or relation using experience from training data and classifying the testing data by the same model or mapping or relation. Equation 1 gives a concise but complete definition of a machine learning model that uses classification. Let a data set D is described by a feature set A= {A1, A2…Am} and sample set S = {S1, S2...Sn} with m number of features and s number of samples. Let us further assume a machine learning framework can be defined by a model L which predicts the class C with accurate prediction (Q). The prediction is evaluated by performance measure (P) in such a way that error (Err) is minimized over all training samples during training phase and all testing sample during testing phase [40].

\[
P \rightarrow \min_c [Err\{c - Q[L(\sum_{i=1}^{n} \sum_{j=1}^{m} D(Ai, Sj))]]\]  

(1)

The performance measures can be any metric like accuracy, specificity, sensitivity, recall, precision and area under the curve (AUC). These performance measures act as comparison operator between various machine learning models like decision tree (DT), support vector machine (SVM), artificial neural networks (ANN), k-nearest neighbor (k-NN), Bayesian classifiers etc.

3.1. Recent Methodologies used in ML Framework-A

Preprocessing appears to be common abstract step in all the kind of frameworks with different concrete functionalities. Framework-A is presented in Figure 2. The preprocessing involves filling of missing values and normalization. A common strategy to fill missing values using instance mean while normalization is often performed using min-max normalization [41]. Feature selection is next step in the framework which very crucial step as it accelerates the procedure of building a machine learning (ML) model that results in increased efficiency and accuracy as well [42]. Principal component analysis (PCA) has been used in feature selection in many recent studies of heart disease prediction [12]. A very recent
and detailed survey has been presented for data preprocessing while classification of heart disease [43].

Next stage is classification which is achieved by various classifiers including decision tree, Bayesian classifier, artificial neural network and support vector machines. Zhou et al. (2021) [42] used a feature weight based feature selection and classification through decision tree. Many methodologies including k-mean and ReliefF are used in preprocessing. Karalaís et al. (2010) [44] evaluated the risk of coronary heart disease through decision tree and classification rules are extracted by identifying most important factor in risk prediction. Alizadehsani et al. (2013) [24] introduced a very much informative dataset for prediction of heart disease. Sequential Minimum Optimization (SMO) Bagging, a training algorithm of SVM, ANN and Naïve Bayes algorithms are trained and tested using 10-fold cross validation and it has been found that SMO bagging has highest accuracy.

| Ref. | Data set | No. of features | No of samples | classifiers | Acc. | Sens. | Spec. | Other measures |
|------|----------|-----------------|---------------|-------------|------|-------|-------|----------------|
|      |          | SPECT(heart), SPECTF, Statlog | 23 | 267 | DT with feature | 67.44, 71.14, 72.74, | -- | 42.89, 46.56, 45.11 |
| [42] |          |                 |               |            |      |       |       |                |
|      |          |                 |               | FAMD-LR, FAMD-kNN, FAMD-SVM, FAMD-DT, FAMD-RF | 91.80, 90.16, 91.80, 81.96, 93.44 | 92.85, 96.42, 100, 96.96 | 92.59 |
| [40] | Cleveland heart | 303 | 14 | Hybrid RF with Linear Model | 88.4 | 92.8 | 82.6 |                |
| [45] | Cleveland heart | 14 | 303 | GA, SVM | 93.3 | 99.5 | 87.1 |                |
| [46] | SPECTF, SAheart | 13 | 270 | SLFN(ELM) with CSO | 86.12 | 78.61 | 75.42 |                |
| [38] | CHS Cleveland heart, Hungarian, Switzerland, VA Long Beach (UCI) | 920 | 14 | Fuzzy Boosting with PSO | 85.76 | 90.02 | 82.31 | 86.48 |
| [47] | Statlog(heart) | 13 | 270 | ANN-CAPS, Bagging SMO | 81.85 | 74.63 | 90.21 | AUC 0.876 |
| [48] | Z-Alizadeh Sani | 54 | 303 | DT | 75 | 73 | 71 |                |
| [44] | Dept of Card.PGH, Cyprus | 14 | 1500 | DT | 75 | 73 | 71 |                |

Table 1. Some Recent Studies on ML Framework-A
In last decade it has been observed that machine learning techniques got improved by when hybridized with a metaheuristics approach for medical diagnosis especially in heart diseases prediction [49]. Such improvements were noted when a single hidden layer Feed forward Neural Network was trained with Competitive Swarm Optimization and Extreme Machine Learning [46]. In an ensemble fuzzy boosting approach for classification was enhanced with Particle Swarm Optimization for heart disease prediction [47]. Table 1 listed some of recent prominent studies that follows the methodology of ML Framework-A. The table contains the reference of the research, name of the dataset used, number of features, number of samples, name and performance measures of the classifier as described by Equation 1.

### 3.2. Recent Methodologies used in machine learning framework-B

Electrocardiographs (ECG) and Phonocardiograms (PCG) represent physiological conditions of the heart through electrical and sound signal respectively [36]. ECG classification is stepwise process that includes preprocessing, segmentation, feature extraction, feature selection and classification[50]. PCG signals classification consist of 3 basic steps which are preprocessing (involves filtering and segmentation), feature extraction and classification [34]. Framework B is depicted in Figure 3 that presents combined workflow of the process used for classification of signal data (ECG and PCG). Some recent studies are summarized for ECG and PCG data using ML Framework-B methodology in Table 2. The table contains reference number of the research work, name of data set, the key preprocessing tasks involved, and name of classifiers with highest accuracy, sensitivity and specificity. The next two subsections explain some recent studies involving ECG and PCG classification briefly.

| Ref  | Dataset                        | Pre-processing techniques                  | Classification technique | Acc | Sens. | Spec. |
|------|--------------------------------|-------------------------------------------|--------------------------|-----|-------|-------|
| [32] | MIT-BIH                        | Shot Time Fourier Transform (STFT)         | CNN                      | 99  | --    | --    |
|      |                                | Welsh method, Discrete Fourier Transform(DFT) | GA-SVM                 | 98.85 | -- | 99.39 |
| [52] | MIMIC-II                       | Gaussian curve fitting, Singular Value Decomposition (SVD) | SVM | -- | 85 | 78 |
| [53] | Long Term ST Database          | Cut of Freq 0.3 Hz (LPF) 20Hz(HPF)         | SVM                      | 99.2 | 98.43 | 100 |
| [54] | PhysioNet 2016 challenge       | HSMM                                      | RF                       | 85  | 80 | 90 |
| [55] | IQRAA Hospital, Calicut, India | FAWT                                      | LS-SVM                   | 100 | -- | -- |
| [56] | IQRAA Hospital, Calicut, India | TQWT,PCA                                  | LS-SVM                   | 99.7 | 99.6 | 99.8 |
| [57] | IQRAA Hospital, Calicut, India | DWT,ICA                                   | GMM                      | 96.8 | 100 | 93.7 |

Table 2. Some Recent Studies on ML Framework-B
3.2.1. Methodologies involving ECG

More steps are involved in ML Framework-B as compared ML Framework-A. It includes preprocessing, segmentation, feature extraction, feature selection and classification. Preprocessing and segmentation are considered in the same stage in the current study. A primary task of preprocessing in ECG is the detection and attenuation of frequencies that are associated with artifacts. Indiscriminate and adaptive filters sometimes distort the actual morphology of signals; hence wavelet transforms are recent trends in preprocessing [58]. Some recent studies used high pass filter, low pass filter, band rejection filter, base line wander and notch filter in preprocessing of ECG data [55], [56]. Normalization and QRS complex enhancement are done prior to the segmentation [50]. Segmentation transforms a signal into the smaller segment signals so that it can be analyzed in a better way [59].

Feature extraction is very important phase of ECG classification. There are some typical ECG features as duration of P wave, PQ /PR/QT interval, QRS width, amplitudes of P/T/QRS and ST level. However, the most common feature used in machine learning is RR interval [58]. Pan-Tompkins algorithm is usually used to analyze R peaks that is ultimately required for RR interval and QRS detection [60]. Das and Ari (2014) presented temporal features and morphological features as two major kind of extracted features. Temporal features are based on RR intervals while S-transform and wavelet transform based features. Pławiak (2018) [51] used power spectral density , Welch’s method, periodogram, Fourier discrete transform , Hamming window and series of logarithms of signals methods to perform feature extraction.

Next stage in framework-B is feature selection which is aimed at selecting most relevant features. The selected features accelerate the classification process and improve the accuracy as well. The performance of SVM classifier was enhanced with linear discriminant analysis (LDA) by classifying ECG signals and achieved a maximum accuracy of 99.88% in a study by Song et al. (2006)[61]. Genetic algorithm was used as feature selection algorithm by encoding genes as 0- to reject a given feature while 1- to accept the given feature. The feature selection is succeeded by SVM, k-NN, probabilistic neural network and radial basis function neural network classification for ECG signals [51]. In another study by Dalal and Vishwakarma (2020) [62] the kernel extreme machine is optimized with genetic algorithm. Deep learning methodologies are also proving its competence for ECG classification now a day. Huang et al. (2019) [32] proposed a 2-dimensional convolution neural network (2-D CNN) based ECG classification system and achieved a significant classification accuracy of 99.00 % in comparison with 1-D CNN (90.93%). Deep neural network has reduced the preprocessing ask to great extent.

3.2.2. Methodologies involving PCG

Phonocardiography is very basic method for recognizing heart sound signals. Phonocardiograms (PCGs) are recorded through phonocardiography. Auscultation of heart sound signals is a primitive but famous non-invasive diagnosis method for heart ailments [36]. Auscultation of heart sound requires a lot of experience and expertise [63]. Recently automated classification of heart sound signals has emerged as a potential research field in artificial intelligence [64]. Classification of sound signals from heart includes 3 process (i) sound segmentation (ii) feature extraction and, (iii) classification. During heart sound segmentation a PCG recording is divided into a sequence of fundamental heart sound signals (FHSs). FHSs are S1 and S2, where S1 occurs at the beginning of systole and S2 occurs at the beginning of diastole [35]. For finding extra sound or murmurs between the periods S1-S2 (systole) or S2-S1(diastole) sound segmentation is done with help of electrocardiogram reference [65].

Identification of first heart sound, second heart sound, third heart sound and fourth sound segmentations are explained with references of various time segments of ECG in a study by Chen et al. (2017)[20]. The interference of noise is avoided by providing envelope features. These are harmonic envelope, Hilbert envelope, wavelet envelope and Power Spectral Density (PSD) envelope. Then duration parameters eHR and eSys are estimated by the envelope feature with some autocorrelation analysis of
PCG [35]. Some initial work on sound segmentation was done by Feldman & Braun and Liang et al. [66], [67]. Recently it is done by Maglogiannis et al. & Schmidt et al. [68], [69].

Feature extraction involves extraction of discriminative features. The features are used subsequently by classifier for classifying the sound signals. The features extracted in PCG classification are based on time or frequency[70], [71]. Some recent feature extraction methodologies involve both the domain i.e., time-frequency domain [72]–[74]. Preceded by sound segmentation and feature extraction respectively the next task (also the final task) done in sound classification methodology is training with the features extracted so as to predict the label of the sound signals. Different classifiers have been proposed for the classification [54], [75]. Deep learning method using convolution neural network found outperforming over DT, Bayesian classifiers, ANN and SVM for PCG classification.

3.3. Recent Methodologies used in machine learning framework-C
Cardiovascular imaging is multimodal in nature that includes X-Ray (Computed Tomography (CT)), Echocardiography, Cardiac Computed Tomography (CCT), Cardiac Magnetic Resonance (CMR), Nuclear Imaging, Single Photon Emission Computed Tomography (SPECT), scintigraphy and Positron Emission Tomography (PET)[76]. Automated cardiovascular image analysis is a revolution for radiologist and it accelerate the diagnosis of the heart problems [22]. Figure 4 summarizes the steps of image classification through ML framework-C. Echocardiography is primary an imaging technique that has low cost. In echocardiography the image is smoothened by filtering the noise which is a part of preprocessing. During preprocessing unnecessary artifacts are removed and the region that contains heart image is selected. Next the features like mean, standard deviation, entropy and texture features are extracted and then ultimately image classification is performed [77]. In scintigraphy and SPECT, perfusion defects are identified with some correlation calculation in rest and stress images. Usually, perfusion is detected by putting some color thresholding. Segmentation and feature extraction are performed thereafter prior to the feature ranking. Feature ranking is a process similar to feature selection that that first ranks various feature according to their discriminative property and then selects the best compact extracted feature subset [78]. Abnormal images indicate presence of heart disease [29].

Echocardiography images are mainly concerned with chamber quantification, ejection fraction and strain measurement, valve images and overall function [76]. In echocardiography the ultrasound imaging can capture the image of arteries suffering from atherosclerosis which ultimately can cause coronary heart disease [79]. Ultrasound imaging is very common low cost and highly reliable non-invasive method in AI and ML [80]. Sudarshan et al. (2015) reviewed and presented concise discussion of commonly used clinical and non-clinical features as well as recent studies of the features to detect myocardial infarction[78]. CMR is used to assess the function and cardiac volumes with better accuracy. Tan et al. (2018) used ANN based fully automated short axis and long axis information to segment the left ventricle image that leads to the in detection of CVD ultimately with improved efficacy[81]. The performance measure used in the study is jaccard index which is used for measuring similarity of image objects. AI based CCT methodologies are used to detect quantification of the artery plaques, flow of blood and coronary artery calcium scoring [76]. In a study, AdaBoost performed better than Naïve Bayes and Random Forest in terms of accuracy, sensitivity, specificity and ROC curve to build an ML model to detect obstructive coronary artery stenoses [82].

PET and SPECT use common methodologies to detect cardiovascular abnormalities using cardiovascular imaging. A very recent study used stress and rest images of 192 patients to constitute a heart image data set for public use like UCI. Knowledge based classification model and deep learning-based model were used to detect perfusion abnormalities with SPECT imaging. Sensitivity is observed as 100% in both the models while accuracy was more in deep learning. However, the shallow features supersede over deep features.
Table 3. Some Recent Studies on ML Framework-C

| Ref  | Techniques        | Type of Imaging | Accuracy | Sensitivity /Specificity | Other performance measure |
|------|-------------------|-----------------|----------|--------------------------|---------------------------|
| [29] | Deep Learning SVM | SPECT           | 93       | 100/86                   | 4.03 sec processing time  |
| [79] | Random Forest     | Echocardiography | --       | --                       | AUC .99 p<0.001           |
| [81] | Neural network regression | CMR            | --       | --                       | Jaccard index 77±0.11, p<0.001 |
| [77] | BPNN              | Echocardiography | 87.5     | --                       | --                        |
| [82] | AdaBoost,PCA      | CCT             | 70       | 79/64                    | --                        |
| [83] | Naïve Bayes, PCA  | Scintigraphy    | 81.3     | 83.7/79.2                | P<0.05                    |

The shallow features were created by SVM. In summary study achieved better accuracy with the confluence of the classical ML model and deep learning model [29]. Detailed discussion of all cardiovascular image classification is beyond the scope of this paper. However, a summary on recent studies is presented in Table 3 for cardiovascular image and heart disease prediction. The table contains the reference number of research paper, techniques used for classification, type of imaging, accuracy, sensitivity, specificity and some other performance measures. These measures are p value, AUC, model building time and jaccard index. The results are statistically significant if the value of p is less than or equal to 0.05. Classification is considered better if the value of area under the curve (AUC) is near to 1 while it is poor below 0.5. The heart image similarity is measured using jaccard coefficient in [81].

4. Discussion

Machine learning techniques have major contribution towards the automated diagnosis of heart disease as it can be seen from the recent studies that are reviewed and highlighted in this study. There are three kinds of data which can be used to build a machine learning model: (i) data based on clinical parameters and physiological parameters (ii) data based on signals and (iii) data based on images of the heart. Depending upon these types, three ML Framework are presented and discussed in this review study. In framework-A the preprocessing is much simpler than the preprocessing in framework-B and C. Given the physiological and clinical parameters and ECG signals the machine learning techniques like ANN, SVM, KNN, DT and Bayesian classifiers works efficiently. Table 1 shows and describes the state-of -art machine learning methods (ML Framework-A) used for heart diseases prediction with modern comparison operators including accuracies, sensitivities, specificities, AUC, F-measures, precision, recall etc. [40]. The accuracies are improving for heart diseases diagnosis if machine learning approaches are being hybridized metaheuristic technique as feature selection algorithms or optimization techniques [46]–[48], [62].

Major focus of researchers while using ML Framework-A is towards feature selection and classification while in Framework-B and C, the feature extraction is a key step. Raw ECG or PCG is of no use if we do not calculate the necessary features and parameters. Bio-signals appear in different complex shapes and finding hidden features are challenging task. Because of signals analysis is common concern, ECG and PCG are considered in the same ML Framework with some difference in feature extraction. RR intervals, QRS duration, mean of RR intervals, standard deviation of successive RR intervals are some...
common features in ECG while PCG signals are analyzed in either time domain, frequency domain or time-frequency domain. Modern studies involve envelope features and duration features for heart sound segmentation that ultimately improves heart disease prediction [35]. It can be observed that SVM and ANN supersede ECG classification. Deep neural networks supersede in PCG classification as per the recent trends. Deep neural network also superseded heart disease diagnosis using cardiovascular imaging. Deep neural networks work well for PCG classification and for cardiovascular image classification. Large number of data repository and ML techniques are available for heart disease diagnosis but still there is a scope of improvement in accuracies and other performance measures.

5. Conclusion
A brief but informative review is done for all kind of data used for heart disease prediction. The contemporary supervised machine learning techniques used in heart disease diagnosis are collected, reviewed and found that there are three major workflows i.e., ML Framework-A, ML Framework-B and ML Framework-C. From the proposed frameworks it has been observed that feature selection play key role in ML Framework-A while the feature extraction plays a key role in ML Framework-B and C. SVM and ANN performs better than all other classifiers in heart disease diagnosis with clinical and physiological parameters (ML Framework-A). In machine learning methodologies that uses raw ECG (ML Framework-B) SVM supersedes all other classifiers. In PCG (ML Framework-B) classification convolution neural network (CNN) based deep neural networks perform well and supersed other classifiers. ML based heart diseases prediction using cardiovascular imaging (ML Framework-C) is a diversified image classification problem which depends on imaging techniques used. SVM, ANN and deep learning methods works well for cardiovascular imaging including echocardiography, CMR and SPECT. It is also observed performance measures depend on type, size and features of dataset used for building ML model. Further, there a key observation in the review that hybridization of metaheuristic approaches improves the classification process in terms of time and accuracies, when used for heart disease diagnosis.

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