Review

Artificial intelligence in the diagnosis and detection of heart failure: the past, present, and future

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Artificial Intelligence (AI) performs human intelligence-dependant tasks using tools such as Machine Learning, and its subtype Deep Learning. AI has incorporated itself in the field of cardiovascular medicine, and increasingly employed to revolutionize diagnosis, treatment, risk prediction, clinical care, and drug discovery. Heart failure has a high prevalence, and mortality rate following hospitalization being 10.4% at 30-days, 22% at 1-year, and 42.3% at 5-years. Early detection of heart failure is of vital importance in shaping the medical, and surgical interventions specific to HF patients. This has been accomplished with the advent of Neural Network (NN) model, the accuracy of which has proven to be 85%. AI can be of tremendous help in analyzing raw image data from cardiac imaging techniques (such as echocardiography, computed tomography, cardiac MRI amongst others) and electrocardiogram recordings through incorporation of an algorithm. The use of decision trees by Rough Sets (RS), and logistic regression (LR) methods utilized to construct decision-making model to diagnose congestive heart failure, and role of AI in early detection of future mortality and destabilization episodes has played a vital role in optimizing cardiovascular disease outcomes. The review highlights the major achievements of AI in recent years that has radically changed nearly all areas of HF prevention, diagnosis, and management.

Keywords

Deep learning; Decision trees; Heart failure; Artificial neural network; Electronic health records; Echocardiography; Mobile health

1. Introduction

Artificial Intelligence (AI) possesses the capability to perform human intelligence-dependant tasks such as receiving perspicuity, learning semantics, and formulating an analysis using various algorithms and cognitive computing [1]. AI uses the concept of Learning, which can be classified into supervised, unsupervised, and re-enforcement. Machine Learning (ML) is the core of AI that uses a model based on training data to make decisions, and program algorithms to solve the problem [2]. The commonly utilized classification models include Binary, Multi-class, Multi-label and Imbalanced Classification. Binary classification uses algorithms like Logistic Regression, k-nearest neighbors, decisions tree, support vector machine and naïve bayes to classify two labels' tasks. Multi-class uses algorithms like decisions tree, support vector machine, naïve bayes, random forest, and gradient boosting to classify tasks involving more than two labels. Multi-label classifies tasks that have two or more class labels, where one or more class labels may be predicted for each example, unlike the multi-class where a single class label is predicted for each example. The class labels with unequally distributed tasks are classified using the Imbalanced classification model [3]. The distributions can vary from slightly imbalanced to severely imbalanced. It constitutes a significant challenge in predictive modelling as algorithms used for imbalanced classification are based on assumptions [4]. Class labels are often string values, e.g., "*spam*", "*not spam*", which are mapped to numeric values in the process of label encoding [3]. Deep Learning (DL) is a class of the ML algorithm that uses higher level features such as neural networks derived from a model of the human brain which allows a computer system to read, build, and learn complex hierarchical representation [5]. It involves the transformation of the input data into a more compounded output data. Genetic predisposition is a major factor in the development of cardiovascular dis-

Table 1. Description of various functions of components of artificial intelligence.

TYPE OF AI	DESCRIPTION
SUPERVISED	Usage of a previously labelled database to predict outcomes of future events.
UNSUPERVISED	Identification of previously un-categorised database to predict peculiar relation between the dataset.
RE-ENFORCEMENT	Interaction of a machine with its environment using sensors, camera and GPS. It is typically used for robotic interventions.
ARTIFICIAL NEURAL	Computing system that analyses and processes information in a similar way compared to the human brain [7].
CONVOLUTIONAL NEURAL	Performs analyses of visual images [8].
RECURRENT NEURAL	Functions by developing connections between nodes from a directed graph along a dynamic temporal sequence [9].

Abbreviations: GPS, global positioning system.

eases such as atherosclerosis and advanced techniques such as the use of DL networks can be used to predict advanced coronary artery calcium through a large-scale genome-wide association study [6]. DL can be further sub-divided into Artificial Neural Network, Convolutional Neural Network, and Recurrent Deep Learning, as shown in Fig. 1. Table 1 [7–9] illustrates the description of the functions of various components of artificial intelligence.

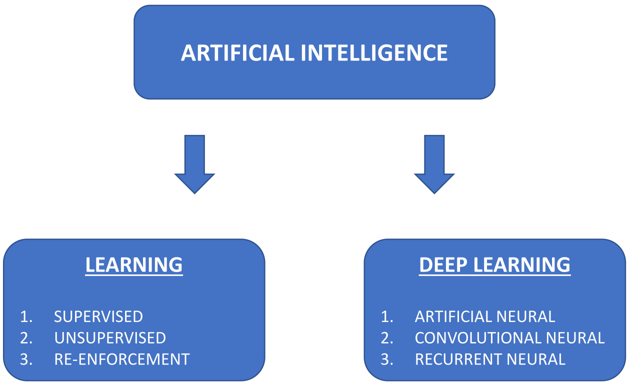


Fig. 1. Classification of Learning and Deep Learning. The concept of learning can be sub-divided into supervised, unsupervised, and re-enforcement. Deep learning comprises complex features including artificial, convolutional, and recurrent neural networks.

The evolution in cardiovascular diseases requires advancements in the treatment and diagnostic techniques, thus AI is now being rapidly incorporated in the field of cardiovascular medicine. AI has the potential to revolutionize the medical diagnosis, treatment, risk prediction, clinical care, and drug discovery through the interpretation of vast databases more efficiently as compared to the human brain [10, 11]. The use of DL-based diagnostic modalities such as cardiac angiography, echocardiography, and electrocardiogram (ECG) in the field of cardiovascular medicine has played a pivotal role in revolutionizing the diagnosis of cardiovascular disorders such as heart failure, myocardial infarction, arrhythmia, and valvular heart disease. Paroxysmal Supraventricular Tachycardia (PSVT) is a sporadic, sudden, and recurrent cardiovascular disorder that can worsen the quality of life of the patients. Although treatable; the condition is difficult to diagnose due to its instantaneous episodes occurring during normal sinus rhythm. However, the use of DML-based ECG has made the early diagnosis of PSVT possible. The use of diagnostic modalities and other AI-based tools such as medical resonance imaging (MRI), intravascular ultrasound, optical coherence tomography (OCT), and single photon emission computed tomography (SPECT) allows clinicians to make a detailed and faultless diagnosis of potentially fatal cardiovascular diseases [12]. Furthermore, the use of ML-based AI has proven to predict 5-year survival rate in patients with cardiovascular diseases, more accurately (80%) as compared to the clinicians (60%) [13].

Heart failure is a major cardiovascular disorder with the mortality following hospitalization being 10.4% at 30 days, 22% at 1 year, and 42.3% at 5 years, despite marked improvement in medical and device therapy [14]. The multifactorial pathophysiology of HF that includes structural and functional abnormalities makes the diagnosis and treatment of HF more difficult. The advent of AI in the field of cardiovascular medicine through diagnostic modalities such as ECG, Echo, angiography, and the use of modern techniques like robotic percutaneous coronary intervention in its management has markedly reduced the mortality of patients with HF. It is unlikely that AI will replace physicians, however, AI can act as an essential tool that can help physicians improve their clinical judgment, and provide a precise diagnosis of diseases like HF. In this study, we aim to discuss the role of AI in the detection and diagnosis of HF. We have also discussed the limitations in the incorporation of AI in cardiovascular medicine, and how it can be further developed.

2. Methods

An extensive literature review was conducted using PubMed/MEDLINE and Cochrane databases from their inception until June 2021 for this review. The following search string was employed: ("artificial intelligence" OR "Machine Learning" OR "Deep Learning") AND ("heart failure"). Google Scholar was also searched to identify grey literature. No time or language restrictions were set. All articles retrieved from the initial search were transferred to Endnote Reference Library (Version X9; Clarivate Analytics, Philadelphia, Pennsylvania) where duplicates were identified and removed. Initially, the search included 26,246 articles, 19,582 duplicates identified between Cochrane and PubMed were removed. A total of 6664 titles and abstracts were scanned, of which 254 studies were found relevant. Further 82 exclusions were made as the full text was not available for these studies. Another fourteen studies were excluded as they were not available in English. A total of 158 full texts was then retrieved, and further 30 exclusions were made as these studies were beyond the scope of this review. The exclusions were made based on studies not being relevant to the utilization of artificial intelligence in diagnosis, classification, prevention, and management of heart failure. Finally, 128 full-text articles were included in this review.

2.1 The role of AI in the diagnosis of heart failure

According to the European society of cardiology (ESC), nearly 26 million people have been diagnosed with HF worldwide [14–16]. Furthermore, 3%–5% of hospital admissions have been attributed to HF incidents. Hence, early detection of the disease is of vital importance in shaping the medical and surgical interventions to reduce the high rates of mortality and morbidity. AI has been reported to correct any existing medication errors, and hence can be effectively utilized as an 'assisting resource' on which clinicians can rely, and use in daily clinical practice [17]. Furthermore, AI and human predictive skills have been compared in previous literature. American Heart Association (AHA) and American College of Cardiology (ACC) provide guidelines on primary prevention of cardiovascular disease using risk factors such as nutrition, obesity, physical factors, diabetes, and lipid profile. In a new study, ACC/AHA guidelines were compared with four machine-learning algorithms: random forest, logistic regression, gradient boosting, and neural networks. The results not only indicated NN to predict 7.6% more events than ACC/AHA criteria but also took into account twenty-two more data points including ethnicity, kidney disease, and arthritis which are not part of AHA/ACC guidelines thus demonstrating AI to be of great value in predicting risks [18]. Another study applied NN for the diagnosis of HF on 40 individuals with the dataset comprising age, gender, blood pressure, and smoking history to determine predictors for HF. The model proved to be highly accurate with 85% of the results correctly predicted [19]. The first-line investigation performed in suspected heart problems is usually ECG, after which the diagnosis gets narrowed down, and if HF is suspected, the physicians investigate for cardiac biomarkers such as natriuretic peptides. However, natriuretic peptides are not very specific markers for HF. Instead, they are subjective to factors such as obesity, age, kidney disease amongst others [15, 20, 21]. Heart failure with preserved ejection fraction (HFpEF) is a rapidly emerging global health issue with its prevalence increasing at a rate of 1% per year relative to heart failure with reduced ejection fraction (HFrEF) owing to risk factors including age, gender, weight, and hypertension.

HFpEF is a complex syndrome resulting from structural and functional cardiac disorders rather than one disease entity hence making it difficult to diagnose by clinicians treating HF patients. Kwon *et al.* [21] established an adequate tool to screen it reliably and economically. The study developed and validated a DL model (DLM) based on an ensemble NN using 12-, 6-, and single-lead ECG that demonstrated reasonable performance. The DLM was further visualized to determine the characteristics and regions of ECG that were used for HFpEF prediction and confirmed the important variable for the decision in other ML models based on logistic regression (LR), random forest (RF), and convolutional neural network (CNN). A sensitivity map was used to identify where DLM focused on primarily, and it was found to have focused on the R wave in the QRS complex as well as the T wave [21]. The study further showed that in the subgroup of 1412 patients without HFpEF at initial echocardiography, 246 patients developed HFpEF within 24 months. Patients whose DLM was defined as having a higher risk had a significantly higher chance of developing HFpEF than those in the low-risk group (33.6% vs. 8.4%, $p < 0.001$). Hence, the application of DLM to echocardiographic and ECG finding for screening HFpEF proved valuable [21]. AI coupled with ECG findings can also be used to highlight patients with HFrEF. A randomized control trial demonstrated AI to diagnose EF <50% in greater number of patients (2.1%) compared to usual care (1.6%) [22].

HeartModel is another modern invention that makes use of echocardiography in allowing consultants to determine disease status and treatment options. It is a software package that provides an automated analysis of echocardiographic findings in terms of echocardiographic parameters such as chamber volumes and ejection fractions [23]. A study conducted on the Chinese population compared the results of automated vs. manual echocardiography. It was found that atrial and ventricular volumes were a bit overestimated by the automated echocardiography device in comparison to manual echocardiography, while left ventricular ejection fraction (LVEF) was the same for both employed methods [23]. Statistical results favored the incorporation of automated echocardiography devices in place of manual echocardiography to assess chamber volumes and ejection fraction to diagnose HF [23].

2.2 Application of logistic regression (LR), random forest (RF), and support vector machines (SVM)

The LR model of AI has been applied in the diagnosis of congestive heart failure (CHF). Son *et al.* [24] included CHF patients presenting with complaints of dyspnea. LR- based decision-making model was used to generate certain decision rules based on predictors of CHF. A decision-relative reduct was selected to generate decision rules using the Rough Set (RS) based decision model. The RS-based model performed much better in the prediction of CHF patients than the LR-based model, with an accuracy of 97.5% and 88.7%, respectively. It was supported by the AUC for the two decision-based models, 97.5 ± 1.1% and 88.8 ± 3.1%, respectively [24]. RF model also provides 100% classification accuracy in detecting CHF. A study conducted by Masetic *et al.* [25]

made use of long-term ECG findings extracted using the autoregressive Burg method. Various classifiers were tested including SVM, artificial neural network (ANN), and k-nearest neighbors (k-NN) amongst which RF algorithm was selected due to a higher level of accuracy, and specificity for the diagnosis of HF [25]. Detection of HF six months before the actual clinical diagnosis was achieved by Wu *et al.* 2010 [26]. The Geisinger Clinic's electronic health records were obtained to be used in the model; 179 independent variables were expressed. The authors used SVM, boosting, and LR methods for HF identification. The study demonstrated that HF was detected more than six months before the actual date of clinical diagnosis using the LR model and boosting. SVM demonstrated the poorest performance, possibly owing to imbalanced data [26].

2.3 Risk level assessment using decision tree classifiers

Decision-making models involving decision trees have been utilized for the diagnosis of CHF in patients presenting to the emergency department. Rough sets (RS) and LR methods have been used to construct a decision-making model with the RS-based model proved to be more accurate than the LR model [24]. Aljaaf *et al.* 2015 [15] put forward a 5-risk level assessment (1 = no risk and 5 = extremely high risk) for HF prediction by making use of the C4.5 decision tree classifier [15]. The dataset used for the project was further improved by considering lifestyle factors such as obesity, physical activity, and smoking. The cumulative accuracy for the 5 risk levels was observed to be 86.3% [15].

2.4 Least-squares support-vector machines (LS-SVM) application with ML

The heart responds to stimuli from inside and outside the body, which eventually leads to heart rate variability (HRV). The usage of ECG in HRV has limitations because HRV analysis in identifying cardiac problems is usually incomplete. By using linear and nonlinear HRV findings, the accuracy of results can be improved [27]. Linear Autoregressive (AR) makes use of the frequency and time domain. The time-domain makes use of R-R interval, while the frequency domain uses the oscillation analysis of 5-minute ECG recordings or the Holter ECG, which monitors heart rhythm throughout the day [28]. Nonlinear AR takes the humoral, electrophysiological, and hemodynamic variables, etc. into consideration. Support vector machines (SVM) can also be utilized for the detection of CHF as a study demonstrated it to be amongst the top three classification methods with an accuracy rate of nearly 98%. This study analyzed ECGs for normal rhythm, SV arrhythmia, and CHF amongst hundred patients. Vectors were employed for this purpose comprising SVM, artificial neural network (ANN), C4.5 decision tree, and RF which then underwent clustering and classification. Another study was conducted to explore the nonlinear AR in further detail, where the analysis of the spectrum was instead using ML models such as SVM, decision trees, k-NN, and ensemble classifiers. SVM was used with its kernel, enabling it to take data as input and transform it into the required form, i.e., linear, Gaussian, linear base function, and polynomial. This study also reported SVM to demonstrate the highest performance amongst the different methods employed [29]. Finally, Zheng *et al.* 2015 [30] introduced a computer-assisted system and made use of the least-squares SVM (LS-SVM), which utilized heart sounds and cardiac reverse features. The results showed ANN and Hidden Markov Models to be dominant over the LS-SVM model.

2.5 Expert driven knowledge, ML and DLM

The role of AI in assisting HF specialists in diagnosis can be made easy by potential assistance from Artificial Intelligence-Clinical Decision Support System (AI-CDSS) [31]. It is a hybrid system that contains both expert-driven and ML-driven knowledge to grow the knowledge base with HF [31]. Retrospective cohorts and prospective pilot studies with HF and non-HF patients were carried out to observe the accuracy of AI-CDSS, which was converted into mind maps and then to a decision tree to be assessed by physicians [31]. Machine-derived learning involved the usage of 5 algorithms that selected LVEF left atrial volume index (LAVI) and left ventricular mass index (LVMI) as contributing factors [31]. All algorithms were ranked for accuracy, the number of rules extracted, and the number of attributes involved [31]. The classification and regression tree (CART) algorithm was selected owing to its highest accuracy. Combining the two methods (ED and ML), lead to hybrid knowledge, the clinical knowledge model (CKM), which focused on the physical findings in patients, while a prediction model from ML looked for LVEF. The overall diagnostic accuracy was found to be 90% (expert-driven), 88.5% (ML-driven) and 98.3% (hybrid CDSS) [31]. Direct learning can assess complicated patterns in dataset more than NN, which is why DL is being incorporated more often in the field of medicine [20]. These models have also been studied for diagnosis of HF using chest X-rays. Matsumoto *et al.* [32] used 952 chest x rays and established a DL model with an accuracy of 82% for HF detection.

2.6 Modern-day use of sensors in measuring patient vitals and implementation of IoT

Modern and compact implanted sensors are highly efficient in measuring vitals that are highly specific to HF's course and prognosis. These sensors are wireless and battery-less. Raised Left Atrial Pressure (LAP) is the earliest and most specific sign of HF before any symptoms appear. Implantable sensors can now easily record LAP and print a waveform. V-LAP is amongst the first battery-less cardiac monitoring devices which track LAP and provides remote HF care in such patients [33]. With the help of V-LAP, physicians can now continuously monitor a patient's LAP and identify HF even before the onset of HF symptoms [33]. In recent years, pulmonary artery pressure (PAP) measurements at home have been possible through the implantation of pressure sensors in the pulmonary artery. CardioMEMS system is a monitoring device most commonly utilized to measure PAP [33]. It was used in the CHAMPION trial and a 33% decline in cardiac hospitalizations was noted over 18 months [34]. Apart from measuring PAP, devices such as defibrillators and pacemakers have shown inefficacy in preventing hospitalization/rehospitalization in contrast to the CardioMEMS [35]. The level of physical activity determines the course of HF to a great extent. Informative accelerometers are non-invasive devices that can be used to track the physical activity of HF patients which has been found to predict the risk of hospitalization [33]. Remote Dialectic Sensing (ReDS) uses electromagnetic waves to detect the extent of pulmonary congestion which infers lung field concentration, helping in the interpretation of CT scans of lung field concentration [33].

Various objects around us have been incorporated with an electronic software broadly termed the internet of things (IoT). It consists of 3 layers, a sensing layer that is present in the particular sensor used by the patient, a transport layer which is composed of connectors transporting data from sensor to remote device, and an application layer which is the server [36]. Physicians with the help of IoT can now monitor various vitals in their patients and forecast medical emergencies. This way, patients can now have medical care available at their doorstep, reducing the frequency of hospitalizations. When combined with specific algorithms, IoT can also warn us of heart attacks beforehand [36]. Cardiac resynchronization therapy (CRT) devices can additionally detect intrathoracic impedance, which further helps in predicting hospitalization in HF patients [37]. The MultiSENSE study presented an algorithm based on data from CRT defibrillators which showed 70% sensitivity in hospitalization prediction [38]. To avoid false-positive predictions in HF, the research highlighted this issue and provided that a telephone triage questionnaire can easily eliminate false-positive results [39]. Multisensor Non-invasive Remote Monitoring for Prediction of Heart Failure Exacerbation (LINK-HF) study made use of a non-invasive sensor placed on the patient's chest using adhesive tape. The sensor could record ECG, 3-axis accelerometry, skin impedance, body temperature, and posture [40]. The Bluetooth-enabled connection between the sensor and cellular phone allowed for data transfer. Data-enabled cell phone syncs the transferred data to an encrypted cloud for viewing and storage. Cloud-based data gets converted to similarity-based modeling (SBM), and a baseline model is constructed within 72 hours of hospital discharge. Following this, the sensor on the patient's chest switches to the scrutiny phase and monitors the vitals [40]. Variations in vitals due to normal activities are noted to remove false alarms. This is done by creating a multivariate change index range, from −1 to 1. The change in the patient's physiology would indicate a greater index change, while no change in physiology would be closer to 0. The change in index range (−1 to 1) allows for continuous monitoring of patient's vitals and provides indications for rehospitalizations [40].

2.7 Derivation of DEWS using TTS and RRS

To manage and prevent in-hospital cardiac arrest, a track and trigger system (TTS) and rapid response system (RRS) were introduced to identify cardiac arrest. Although TTS proved to be of great help, it was associated with high false alarms and low sensitivity. Single parameter TTS is defined as when anyone's vital sign concerning the heart, i.e., blood pressure, heart rate, respiratory rate, body temperature, and mental status is found to be abnormal [41]. To avoid a high rate of false alarms, a deep learning-based early warning system (DEWS) was introduced. This system has better sensitivity and a low rate of false alarms. The DEWS make use of ML by identifying trends in the dataset, including specific vitals, as mentioned above [42]. The model was used in two hospitals, a cardiovascular teaching hospital, and a community general hospital. Patients who had cardiac arrest had experienced death within 30 minutes of admission, or who were outside the study period were excluded. DEWS is a 3 layered neural network system which makes use of the time series data [42] by going over records to conclude a patient's current state. DEWS was compared with modified early warning score (MEWS) at 3 sensitivities and SPTTS at 1 sensitivity. It was also compared with logistic regression and random forest at 75% sensitivity [43]. The area under the receiver operating characteristic curve (AUROC), the area under the precision-recall curve (AUPRC), and confidence intervals (CIs) were greater for DEWS compared to other models [42]. The specificity, positive and negative predictive value, F measure, MACHP, and net reclassification value were assessed using 75% sensitivity. DEWS was found to be the most accurate amongst all systems, hence DEWs can be used in the RRS to identify cardiac arrest [42, 43].

2.8 Classification of HF

Algorithms can be used to classify HF into many types in the same way they have been used to diagnose patients with HF, well beforehand, and prevent hospitalization. Unsupervised ML performs grouping, i.e., observes similarities in the total dataset and compiles similar data in one place whereas supervised ML identifies trends and predictions [5, 44]. A study used model-based clustering (MBC) to classify HF in different phenotypes. HFpEF patients were taken in the study along with their variables such as echocardiography and laboratory results [45]. MBC made use of R in the mclust package. After the application of MBC, classifiers were made to assign patients in their respective groups using Elastic Net, Neural Networks, and Naive Bayes. Resampling was done using cross a validation procedure in which four-fifth of the sample was used in the optimization of the model parameters, while the remaining of the sample was used in the prediction performance assessment, i.e., the ability of the ML model to put samples in the correct phenogroups [45]. Six phenogroups were identified via MBC; phenogroup 1 consisted of young patients with cardiovascular risk factors, including left-sided heart changes along with patients that progressed to chronic kidney disease. Phenogroup 2 patients included severe HF with the highest degree of diastolic dysfunction, and deteriorating right ventricular function. Phenogroup 3 included young patients with milder HF variants. Phenogroup 4 included male patients with hypertension and enlarged left atrium contributing to the risk of atrial fibrillation. Phenogroup 5 and 6 included females with hypertension, atrial fibrillation, and low body mass index (BMI) [45]. After establishing the protocol, a test run was carried out by clustering patients and using Elastic Net to put them into phenogroups accordingly [45].

In another study, unsupervised clustering was used with the addition of CRT devices. The variables including echocardiography values were recorded, and the ML algorithm was used, after which the samples were clustered using the K-algorithm to identify 4 phenogroups undergoing CRT [44]. Phenogroups 1 and 3 involved females with cardiomyopathy and left bundle branch block (LBBB), while phenogroup 1 was found to have prolonged QRS interval in comparison. Phenogroups 2 and 4 involved males with HF, predominantly caused by ischemia but had a lesser percentage of patients with LBBB [44]. Cluster analyses on patients with HFpEF using exercise tolerance have also been performed in published literature. A study included HFpEF patients who underwent echocardiography during rest and following exercise to monitor heart function at both states. Clustering was done of noted variables which lead to the separation of the total dataset into two distinct phenogroups based on data similarities and differences. The first phenotype had a decreased chronotropic/diastolic reserve, ventricular arterial coupling (indicating global heart efficiency), and abnormal longitudinal deformity, while the other phenotype showed a preserved heart rate reserve combined with low left ventricular systolic reserve [46]. Few studies have classified HF using conventional tress and ML classifiers. Classification trees divide the total dataset into many subsets but are found to have questionable accuracy, while ML uses an aggregate of classification trees [24]. Classification trees are simple to use and can utilize binary methods to dividing the dataset into two subsets. The classification of HF has been performed in two parts in a study with all classification techniques used in a manner to keep two classifications as their result, i.e., HFpEF and HFrEF.

The bootstrap technique, also known as bagging is a modern technique that has been previously implemented in literature. Multiple bootstraps were applied to the sample size, and a classification/regression tree was utilized for each bootstrap. The bootstrap samples were compiled with help of majority votes in each sample, and the classification was obtained [24]. Boosting classification technique makes use of multiple weak classifiers and "boosts" their result. A weak classifier has a margin of error slightly better than of guessing [24]. When a classifier puts a subject in the wrong class, the class gets weighted heavier hence at the end when it's all summed up, the samples get correctly classified and placed in subsets [24]. SVM makes use of the hyperplane concept, where the dimensional space gets divided into two distinct planes. Hence two distinct subgroups are made in a single sample. The sample on one side of the hyperplane and the one on the other side are considered as two classifications in a sample [47].

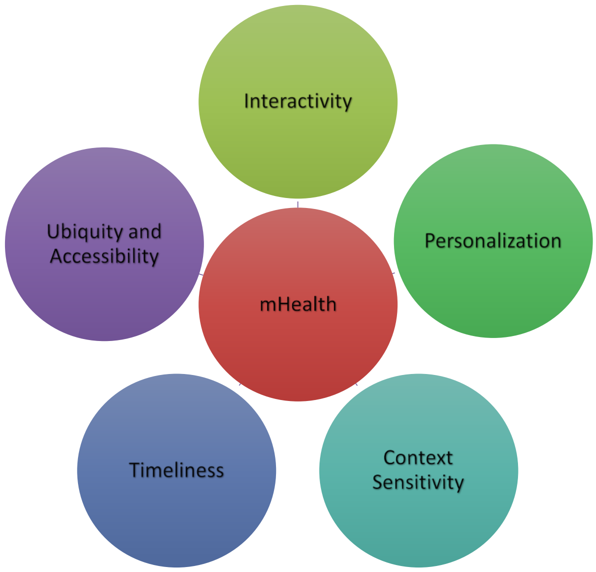
2.9 Role of mobile health and internet of things in the early detection and management of heart failure

AI can be of advantage in identifying potential cardiac events faster than a clinician could, using predictive analytics. As described above, ML; the most common application of AI, can recognize patterns in data to improve cardiovascular diagnosis and detection [11]. Mobile health and the internet of things have allowed patients to keep a track of their health parameters, which have been particularly useful for home-based long-term monitoring, detection, and subsequent alertness for abnormal cardiovascular findings, and timely contact with doctors when necessary.

2.10 MOBILE HEALTH (mHealth)

According to the World Health Organization (WHO)'s Global Observatory for eHealth, Mobile Health (mHealth) is defined as "medical and public health practice supported by mobile devices, such as [cell] phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices" [48]. mHealth enables patients to track their health, e.g., in the form of keeping a check on their heart rate, blood glucose levels, medication dosages, and sleep cycles. It also allows for remote consultations and maintaining electronic health records [49]. It has also been used in managing chronic diseases such as diabetes, hypertension, and chronic obstructive pulmonary disease [50]. The mHealth-based interventions have several factors, potentially making them effective for cardiovascular disease; according to Dicianno *et al.* [51], these factors include: (i) 'interactivity that allows the bidirectional communication and the care delivery, as a form of a personal coach', (ii) 'personalization' that allows for the mHealth interventions to be customized according to the individual's needs, (iii) 'timeliness' which allows for delivery of information within the right time frame, (iv) 'context sensitivity': the ability of interventions to be adapted and modified according to the circumstances and/or the individual's needs, and (v) 'ubiquity and accessibility of the technology to all segments of population' [51]. The advantages of mHealth in the management of HF has been demonstrated in Fig. 2. In addition, wearables (e.g., smartwatches, wristbands, patches and sensors) are being used to measure and record a range of parameters, such as heart rate, blood pressure and temperature, and to track diseases such as HF and diabetes [52]. Wearables not only track and transfer biometric data into a shareable and comprehensible user interface but also allow for the continuous monitoring of more than one dozen biometric parameters as reported by several developers of wrist-worn sensors [53].

A study conducted in 2019, under the collaboration of Stanford University and Apple, assessed the ability of a smart-



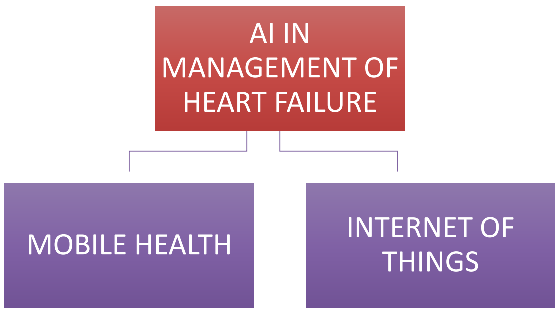


Fig. 2. The advantages of mHealth in the management of HF. mHealth based interventions has been effective in managing cardiovascular diseases owning to the various benefits including interactivity, personalization, context sensitivity, timeliness, ubiquity, and accessibility, adapted from [51].

watch to detect atrial fibrillation or atrial flutter using algorithms that use pulse wave data detection of these episodes [48]. According to this study, only 0.52% (2161) of the total participants received an irregular pulse notification. Among those who received an initial notification and returned an ECG patch, it was reported that 84% of their subsequent notifications were confirmed as atrial fibrillation. Moreover, 76% of the participants who received notification were reported to have contacted either a telemedicine provider or a non-study healthcare provider.

According to a meta-analysis conducted in 2020 among HF patients (n = 1683), mobile phone-based interventions were associated with a significantly lower rate of all-cause hospital admissions at six months (31% vs. 36%, OR 0.77, 95% CI 0.62–0.97, p = 0.03, I^2= 0). A significant difference was also demonstrated for HF admissions (14.0% vs. 18.5%, OR 0.69, 95% CI 0.48 to 0.98, p = 0.04, I^2 = 26%) [54]. However, another meta-analysis found mobile monitoring interventions, mostly consisting of a mobile communication device, a blood pressure measuring device, a weighing scale, and an ECG recorder, to be inconclusive for monitoring HF outcomes. It is also difficult to achieve a 100 percent adherence to mHeath based interventions, as seen in many study groups reported by this meta-analysis, with only one study reporting 100% adherence [50]. However, the popularity of mhealth and its potential utilization cannot be undermined since, in the US alone, 91% of adults have been reported to own some kind of cellphone, with 56% reported to be smartphone users [48]. Moreover, a study conducted in 2017 also stated that older individuals had a positive outlook towards the benefits of mHealth and were eager to utilize mhealth interventions, despite facing usability issues with mHealth such as in navigation and visualization, etc. [55].

2.11 Internet of Things (IoT)

The Internet of Things or IoT is simply a network of different devices in various physical objects or locations, that allows for the exchange and storage of data, using network connectivity [56]. A study conducted in 2017 proposed the structure of an IoT-based system comprising of 3 different layers: the sensing layer, the transport layer, and the application layer, and 4 different modes that could be utilized for heart-disease monitoring. This system could allow for more cost-effective and efficient transmission of data, enabling communication with healthcare practitioners in real-time, in a more structured and systematic way [36]. For cardiovascular management, IoT enables healthcare practitioners to monitor their patients remotely and in real-time, and to collect data, such as blood pressure, pulse rate, oxygen saturation, and ECG simultaneously. This could drastically change the way patients receive medical assistance, making it easier for them to get healthcare at their homes in a timelier fashion, reducing hospital visits concurrently. If IoT is utilized in cohesion with certain real-time algorithms, this could be helpful to alert about potential attacks beforehand [5].

IoT is particularly useful in the detection and diagnosis of certain conditions that may require monitoring throughout the day. To make an accurate diagnosis for arrhythmias, for example, the patient's ECG needs to be monitored for an entire day, at minimum. Hence, making them especially challenging to detect. Moreover, they can be intermittent, so detection and diagnosis can be markedly enhanced by long-term continuous monitoring, using IoT techniques. According to an article published in 2019, mobile cardiac telemetry (MCT) devices that providing real-time monitoring of a patient's heart rhythm over a longer period are essential for AFib detection. MCT devices are the only heart monitoring devices that provide complete arrhythmia detection, with the highest diagnostic yield at 61%, compared to Event monitors at 23% and Holter monitors at 24% [57]. In a study conducted by J. Stehlik *et al.* [58], it was suggested that non-invasive devices such as wearables may be more useful and cost-effective in predicting and recognizing the risk of rehospitalizations for heart failure.

Table 2. Utilization of AI using images obtained from echocardiography.

#	Study	Description	Merit
1	Oritz *et al.* [65]	Neural networks imputed with electrocardiographic data were used to predict one-year prognosis in HF patients.	Prediction
2	Sengupta *et al.* [66]	Utilization of (STE) data for prediction of constrictive pericarditis and restrictive cardiomyopathy.	Differentiation and prediction of CVDs
3	Moradi *et al.* [67]	To closely relate electronic medical records with electrocardiographic images.	Identification
4	Narula *et al.* [68]	Incorporated a similar STE data in a supervised learning algorithm to differentiate athlete heart and HOCM	Differentiation and prediction of CVDs
5	Medvedofsky *et al.* [69]	3D echocardiography for measurement of left ventricular EDV, ESV, EF, and LAV at end-ventricular systole using an automated adaptive analytics algorithm.	Accurate measurements
6	Khamis *et al.* [70]	Use of ML in the automatic apical view classification of echocardiogram.	Automaticity
7	Przewlocka-Kosmala *et al.* [46]	Use of ML to study the relationship between exercise intolerance, and left ventricular systolic function in patients with HFpEF.	Differentiation and prediction of CVDs
8	Ouyang *et al.* [71]	Video-based DL algorithm that used videos and images from an ECG to accurately conclude left ventricle segmentation and ejection fraction.	Segmentation of cardiac structures

2.12 Imaging techniques utilized with AI

ML techniques including supervised and unsupervised networks as well as DL has been incorporated in different cardiac imaging procedures for accurate quantitative and qualitative evaluation of cardiac diseases, particularly, HF.

2.13 Echocardiography

ML models have been trained to recognize specific images of a wide variety of cardiac diseases [59]. This helps in the interpretation of unused data in three-dimensional imaging, thus leading to faster analysis and better outcomes. Furthermore, DL has been mostly utilized in imaging for segmentation of the ventricles. Chen *et al.* [60] demonstrated the use of convolutional neural networks (CNN) to segment the ventricle into 5 different 2D views. ANN model was previously used for segmentation which was further extended in studies by Carneiro and Nascimento [61]. Dong *et al.* [62] and Ghesu *et al.* [63] also combined DL with traditional methods to segment the left ventricle and the aortic valve. Dezaki *et al.* [64] utilized electrocardiograms in combination with RNN and CNN to predict end-systolic and diastolic volume. Table 2, Ref. [46, 65–71] identifies some models for prediction, differentiation of cardiovascular diseases, accurate measurement using echocardiography features providing increasing automaticity, and the ability for segmentation of cardiac structures.

2.14 Cardiac MRI

AI and ML algorithms have proved to be of crucial importance in other imaging techniques like Cardiac MRI particularly for ventricular segmentation. Machine learning (ML) can segment the heart chambers from Cardiac MRIs and these segmentations yield imaging biomarkers to predict CHF. Laser *et al.* [72] used knowledge-based reconstruction of the right ventricular volumes using images from echocardiography and cardiac MRI and compared them with the gold standard direct cardiac MRI and found that knowledge-based reconstruction has excellent accuracy for right ventricular 3D volumetry. Right ventricle has a complex shape which many times could not be visualized with 2D imaging echocardiography techniques. 3D visualization and cardiac image reconstruction with the help of AI can help in the diagnosis of a variety of similar diseases. Similarly, calculation of left ventricular mass, papillary muscle identification, common carotid artery, and descending aorta measurements with fully automated AI programs have produced far more accurate results. Another study extracted CMRIs from 350 subjects and used CNNs to segment the heart in short and long axis Cardiac MRI. He concluded that cardiac MRI provides a reliable method of extracting indicators for cardiac measurements and function [73, 74]. Table 3, Ref. [13, 72, 75–81] summarizes the findings of studies that utilized DL and SVM models using images obtained from Cardiac MRI.

2.15 Cardiac computed tomography (Cardiac CT)

ML based image analysis has been increasingly used for cardiac CT specially for evaluation of coronary artery disease and atherosclerosis. ML models were used for coronary artery calcification scoring and risk stratification. Commandeur *et al.* [82] used 2 CNNs to segment epicardial and thoracic adipose tissue using cardiac CT images. They evaluated their method in a large cohort of 1638 patients. Multi scale patch-based CNN was also used by Zerik *et al.* [83] to segment the left ventricle myocardium. Wu *et al.* [84] used short term memory RNN to label segments of coronary artery tree. Itu *et al.* [85] and Coenen *et al.* [86] also used ML models for quantitative analysis of fractional flow reserve in coronary artery disease. The implication of ML models using datasets from Cardiac CT has played a major role in diagnosis of coronary artery stenosis, and risk stratification of future events.

2.16 Electrocardiogram

ECG is the most widely used diagnostic modality for detection of heart diseases. The application of ML models par-

Table 3. Utilization of DL and SVM models using images obtained from Cardiac MRI.

#	Author	Findings
1	Avendi *et al.* [75]	Cardiac MRI datasets can be used to develop DL algorithm for right ventricular segmentation.
2	Dawes *et al.* [13]	Supervised learning of 3D patterns of systolic cardiac motion can be used to predict death and adverse outcomes in patients with pulmonary diseases.
3	Puyol-Antón *et al.* [76]	MRI and echo dataset used in combination for diagnosis of dilated cardiomyopathy with an accuracy of 0.94.
4	Bernard *et al.* [77]	Used CNNs for automatic segmentation of left ventricle.
5	Luo *et al.* [78]	Used Multiview CNNs for prediction of left ventricular ejection fraction using images obtained from cardiac MRI.
6	Bratt *et al.* [79]	Proved that CNN based segmentation was superior to conventional methods.
7	Kong *et al.* [80]	Used cardiac MRI to detect ES time point.
8	Schlemper *et al.* [81]	Showed that series of CNNs are superior to undersampled dynamic cardiac MRI.
9	Laser *et al.* [72]	Observed that knowledge-based reconstruction has excellent accuracy for right ventricular 3D volumetry.

ticularly DL has helped reduce the time taken in diagnosis, and speed up urgent care. Supervised learning models have been used to classify heart rhythm. Algorithms involving unsupervised learning analysis have also been used. In this method, unlabeled data has been grouped according to its ECG phenotype. This was demonstrated by Lyon *et al.* [87] who classified ECGs with arrhythmia risk factors in patients of cardiomyopathy. Hannum *et al.* [88] used a 34-layer deep NN to classify 12 different types of arrhythmias. Attia *et al.* [89] used a 6-layer deep NN to diagnose left ventricular systolic dysfunction. In this study, investigators attempted to diagnose asymptomatic left ventricular dysfunction by EKG alone using an AI-based CNN deep learning method. This model proved to be superior to the conventional method of using BNP levels for estimation.

2.17 Prediction of adverse outcomes

Early detection of future mortality and episodes of destabilization can help provide quality care earlier in the management of the patient and also allow doctors to make crucial clinical decisions when needed. Using statistical analysis, multiple risk calculation scoring systems have been formed for estimation of mortality.

2.18 Decompensation

Candelieri *et al.* 2008 [90] used knowledge discovery (KD) models to predict if a patient with HF in a stable phase would decompensate or not. A group of 49 CHF patients was used for the evaluation of the KD approaches. Decision trees, Decision Lists, SVM and Radial Basis Function Networks were used, and the leave-patient-out approach was followed to evaluate the performance. Of the models, decision trees proved to be superior to other models and provided an accuracy of 92.03%, sensitivity 63.64%, and False Positive Rate 6.90%. In 2009 Candelieri *et al.* [90] used decision trees and SVM on an independent testing. Their results showed that SVM is more reliable in predicting decompensation events with an accuracy of 97.37%, 100.00% sensitivity. This was further extended through the "SVM hypersolution framework" which proved to be more accurate on minority class than Tabu search. Guiti *et al.* [91] also predicted the frequency of HF decompensation during the year after the first visit using five machine learning techniques (NN, SVM, Fuzzy -Genetic Expert System, Random Forests and CART). CART algorithm proved to be the superior one with 87.6% accuracy.

2.19 Re-hospitalizations and mortality

Re-hospitalizations add to the burden on the healthcare system and lead to poor quality of life for the patient. Predictive models have been developed to predict the risk of future hospitalization so that adequate monitoring and management can be done to prevent such adverse outcomes. At the same time, mortality can be improved using risk prediction models and discrimination of patients as demonstrated in the studies shown Table 4, Ref. [92–104]. Table 5, Ref. [5, 13, 24, 25, 30, 31, 34, 37, 40, 42, 44–47, 51, 66, 69, 71, 75, 88, 105–128] provides the summarized evaluation of the advantages and limitations of some of AI models and devices for HF.

3. Conclusions

HF is associated with poor patient's outcomes, high recurrence rate, mortality rate, and cost burden. There has been a major development in the field of cardiovascular medicine with the incorporation of AI in diagnostic modalities, outcome-predictions, and management of HF. Incorporation of AI Deep Learning components particularly ANN and CNN for diagnosis of HF coupled with remote monitoring of at-risk patients via IoT and mHealth can drastically reduce mortality associated with all structural heart diseases, particularly HF. Though AI has the potential to revolutionize medical diagnosis, treatment, risk prediction, clinical care, and drug discovery through interpretation of vast database more efficiently as compared to the human brain, it has its limitations due to the absence of a healthcare system that supports it, as well as a shortage of trained clinicians who can utilize AI models in their clinical decisions, and monitoring of patients. Therefore, it is essential to establish a connection between AI models and clinical practitioners through hybrid expert, and ML-driven systems such as the AI-CDSS to provide more accurate outcomes. AI systems can certainly not replace the expertise of a human brain but it has the potential

Table 4. Utilization of AI to predict re-hospitalizations and mortality.

#	Study	Prediction	Time period	Classification/Model used
Re-hospitalization				
1	Zolfaghar *et al.* [92]	Prediction of the risk of readmission for CHF	30 days	Random Forest
2	Vedomske *et al.* [93]	Prediction of unplanned readmission for CHF	30 days	Random Forest
3	Shah *et al.* [94]	Prediction of HF hospitalization in HFpEF phenotype groups	-	Support Vector Machine
4	Roy *et al.* [95]	Identification of CHF patients who are likely to be readmitted after discharge	30 days	Dynamic Hierarchical Classification
5	Koulaouzidis *et al.* [96]	Prediction of heart failure admission based on TM data like weight and diastolic BP	Highest predictive performance at 8 days	Naïve Bayes
6	Kang *et al.* [97]	Examination of risk factors for readmission of HF patients	60 days	Decision tree
7	Tugerman *et al.* [98]	Prediction of hospital readmissions of CHF patients	30 days	C5.0 and Support Vector Machine
8	Kawai *et al.* [99]	786 machine learning tools were used to predict HF readmissions	30, 90, and 12 months	Generalized linear model (GLM), boosted GLM, Bayesian GLM, Adaboost.M1 with bagging algorithm (Adabag), Naïve Bayes classifier, random forest and support vector machines
Mortality				
1	Austin *et al.* [100]	Predict mortality of patients admitted for either AMI or CHF	30 days	Ensemble classifiers
2	Subramanian *et al.* [101]	Predicting HF mortality using data with circulating levels of TNF and IL-6, and their receptors sampled at baseline, and at 8, 16, and 24 weeks from Vesnarinone Evaluation of Survival Trial	30 days and 1 year	Ensemble classifiers
3	Panahiazar *et al.* [102]	Heart failure risk prediction	1, 2, and 5 years	Decision Tree, Random Forest, AdaBoost, Support Vector Machine, and Logistic Regression
4	Taslimitehrani *et al.* [103]	EHR-driven HF risk prediction	1, 2, and 5 years	CPXR (Log) Classification Algorithm
5	Ramirez *et al.* [104]	Classification of CHF patients to discriminate between sudden cardiac death and pump failure death using ECG-derived risk markers	-	Support Vector Machine

Abbreviations: CHF, congestive heart failure; HF, heart failure; HFpEF, heart failure with preserved ejection fraction; TM, telemonitoring; BP, blood pressure; AMI, acute myocardial infarction; TNF, tumor necrosis factor; IL-6, interleukin-6; EHR, electronic health record; ECG, electrocardiogram.

Table 5. A summarized evaluation of the advantages and limitations of some of AI models and devices for heart failure.

DIAGNOSIS OF HEART FAILURE CardioMEMS^{TM}:	
ADVANTAGES	LIMITATIONS
Most efficient system till date [105]	Mandatory compliance for pressure management
Reduced hospital admissions [106]	Invasive Implant
Reduced charges per hospitalization	Expensive
Increases patient engagement, which improves the patients' adherence [107] and satisfaction [108]	Needs a new proper system of telehealth to support it
Less direct patient and indirect patient cost [109, 110]	
Intelligent Heart Disease Prediction System Using Data Mining Techniques:	
Reduce patient care cost [110]	Requires structured data while most of the data which is available, is in unstructured form [111]
Can help train medical staff and medical students about diagnoses of heart-failure [112]	Needs more attributes than currently employed for making a comprehensive diagnosis [110]
Helps doctors make decisions	Needs continuous form of data in some cases, and not categorical form [19]
Prevents early readmissions	
Delivers quantitative results	
Avoids time- dependent performance	
Helps to upgrade knowledge for making a diagnosis, and establishing multivariant relations which might be otherwise challenging for physicians	
AI in ECG and Echocardiography [88, 113, 114]:	
Interpretation of the ECG is not limited by the interpreter's finite knowledge	Training of clinicians is required for its proper use
Can help detect ECG signatures and patterns that are not recognized by human eye	AI–enhanced ECG findings as electronic health records to make them accessible at the point of clinical care is not yet available
Can serve as tool for phenotyping person's cardiovascular health	Can be less accurate than an expert reader in classifying the rhythm of heart even with low-quality tracings [115]
Can guide diagnostic testing	
Can detect arrhythmias with a single lead	
AI's integration in echocardiography can help improve its accuracy	
It can help in recognizing number of disease patterns	
Can help reduce analysis time and increases reproducibility	
Application of Logistic Regression, Random Forest and Support Vector Machines:	
Can help differentiate dyspnea from heart-failure	Loss of information and real value attributes were discretized and variations as number of patients with CHF and Non-CD was relatively small [24]
Can reduce workload from doctors and expenses	May not perform well with more challenging interactions, and over- fitting can potentially lead to the instability of this model [116]
Random Forest algorithm by use of autoregressive Burg [25]:	
Can detect different classes of ECG signals	
Overall performance of Random Forest was better than other existing systems	

Table 5. Continued.

DIAGNOSIS OF HEART FAILURE CardioMEMS™:	
Prediction Model Using electronic health record data (SVP) [117]:	
The search for linear classification decision boundary might not be minor in the lower dimensional input space, but was easier in the higher dimensional feature space	Not able to deal with irrelevant features [117, 118]
It can reduce the cost of computation as only features that are stored are lower dimensional features	It is influenced relatively more by classification imbalance in data than other systems [26]
Boosting:	
Boosting can help decrease training errors [26]	
Overall better performance than SVP	
Risk level assessment using C4.5 Decision Tree Classifier [119]:	
This predictive model performs better than many other existing models with 86.5% sensitivity, 95.5% specificity, and 86.53% accuracy	Other factors can be used and help make better prediction; better feature selection method can be used as well.
LS-SVM application with mL [30]:	
Diagnostic characteristics can evaluate and report physiological, pathological content and also the signals differences' morphology, domain of time-frequency and energy	The study did not include training for heart murmurs
Better suited than existing ones like BP-ANN and HMM	
Shorter training time for optimum structure	
Can estimate global solution	
Can avoid local minimal mistakes	
Artificial Intelligence-Clinical Decision Support System (AI-CDSS) [31]:	
More accurate in OPD settings making it important for diagnosis of HF in absence of HF specialists	Attributes used for PM can differ from variables recommended in available guidelines
Ensures transparency regarding features which leads to decision making by use of white box	More studies are required to further validation of the system in different populations
A Deep Learning Model (DLM) on the basis of NN [120]:	
This can help in monitoring of HF outside the hospital and use HRV signals	Unpredictable decision making
It can also help identify HFpEF	More data is required to better train the system
This model can be applied to smart watch or mobile phones' application which can make it portable and more accessible	
Accelerometer [121]:	
Can describe the frequency, intensity and duration of physical activity	A number of brands do not measure comparably over same protocol
	It fails to assess the movement associated with activity which is not ambulatory, like cycling
Intrathoracic Impedance [37]:	
More adequate in comparison to daily weight monitoring in patients with chronic systolic heart failure	Individual variability in the optimal threshold for the impedance-based fluid index
Higher sensitivity	Individual variability in appropriate follow up window
Less frequent false alarms for worsening heart failure which requires hospitalization	False alarms
Identification of Novel Pheno-groups in HFpEF [45]:	
Feasible	Depends on signs and symptoms, and more well-defined criteria is required for HFpEF phenotype
Good reproducibility	
Can classify patients with HFpEF into distinct sub-groups	
Can help in research intervention for HFpEF	

Table 5. Continued.

DIAGNOSIS OF HEART FAILURE CardioMEMS™:	
Continuous wearable monitoring analytics to predict HF hospitalization/the LINK-HF multicenter study [40]:	
Early diagnosis of imminent HF rehospitalization with accuracy which is comparable to implantable devices	The clinical efficacy and its implication on broader levels needs to be further tested and ensured
It is economically feasible	
It is non-invasive	
Derivation of DEWS using TTS and RRS [42]:	
Better sensitivity than TTS and RRS	Alarm sound does not specify the underlying problem
Relatively lower rate for false alarms	It is not interpretable
The imbalance data is adjusted enough to give better sensitivity	Only considers first cardiac arrest
Majority of predictions were made 24 hrs. before the event of cardiac arrest giving specialists enough time to intervene	
It uses less variables and can be applied to different hospital set ups	
Model-based Clustering [44]:	
It can help in giving an interpretable and clinically insightful classification of a heterogeneous cohort for patients of HF	Have not been tested on larger populations with severe HF
It can also help in making foundation of a platform based on data that can potentially help in identifying subgroups of patients who will be responsive to particular therapies	Human intervention was required for specification of the most meaningful clustering configuration
	Due to the overlap between phenogroups, it loses its ability in zones near the outskirts between groups ('ill-defined situation')
Cluster analysis on HFpEF patients using exercise intolerance [46]:	
Can be helpful as a component of diagnostic protocol in patients suspected with HFpEF	Lack of diversity in populations
	Lack of evaluation of peripheral mechanisms, concomitant effects of drugs not being excluded
	Not applicable for atrial fibrillation and CAD patients
Classification of HF using conventional trees and ml classifiers [47]:	
It can help improve prediction and classification of HF patients according to subtype of disease like HFpEF or HFrEF compared to conventional regression and classification trees	Conventional logistic regression was relatively more accurate to predict the probability of the presence of HFpEF in HF patients than the methods used in the data mining and machine learning literature
The Internet of Things (IOT):	
Promising results in elderly, and patients with chronic diseases	Vulnerable to security risks. There is a need to verify privacy policies of each object while transmitting data [122]
Easy monitoring of patients by physicians, reducing frequency of hospital visits and hospitalization Reduces high costs associated with hospitalizations	Interoperability issues Scalability and availability issues associated with supporting a large number of devices, each having different memory, processing, storage power and bandwidth
It can help forecast HF exacerbation more accurately than invasive devices (LINK-HF)	
ReDS™ [5]:	
Helps in early detection of systemic fluid overload, and also detects pulmonary congestion [34]	Tested on a small number of patients [123]
It is more suitable than CT for the management of recurrent events of HF in recently discharged patients	
Associated with a reduced number of HF readmission rates	

Table 5. Continued.

DIAGNOSIS OF HEART FAILURE CardioMEMS^{TM}:	
V-LAP^{TM} [124]:	
It can help physicians in either detecting exacerbation of heart failure before the onset of symptoms, change therapies, or alter drug doses in order to reduce adverse consequences	It is invasive
Can help reduce hospitalizations accurately	
Mobile Health [51]:	
It can help patients achieve an optimum weight, improve workout and exercise, quit unhealthy behaviors, control blood glucose, and manage blood pressure and lipids	Well-defined universal functional parameters for different applications are required
It can also help detect irregular heart rhythms through the use of digital watch. It can help doctors in decision-making	
Heart failure management includes better interactivity	
It involves customized interventions to meet each individual's demands	
Accessible and highly context sensitive	
HeartModel [69]	
Automated analysis of 3D echocardiography is possible	Applicable on good quality images
Reduces the time taken for analysis, and minimal training is required	Limited the generalizability results which includes user input
Can assess LV and LAV function simultaneously	Low frame rates, especially for single beat acquisition, so not applicable for patients with atrial fibrillation and/or ectopic rhythm
Can acquire exact and reproducible automated estimations of LVEDV, LVESV, and LVEF with clinically non-critical contrasts	Not applicable for patients with atrial fibrillation and/or ectopic rhythm
More accurate than previous versions with lesser biases	
Can perform corrections rapidly	
Better reproducibility than conventional manual measurements in terms of both inter- and intra-observer variability	
Cognitive machine-learning algorithm for cardiac imaging [66]:	
Can differentiate constrictive pericarditis from restrictive cardiomyopathy	Limitations include the fact that selection and ranking of variables and selection are dependent on data and algorithm
Better feasibility and effectiveness of automated interpretations of STE data	Marginal diagnostic gain
Can handle large volumes of data, and integrate it with clinical echo variables	Lacks generalizability
Neural network approach based on echocardiographic data [65]:	
More accurately predict prognosis in HF patients than linear discriminant analysis	Uses black box which compromises transparency and requires computer setup
EchoNet-Dynamic:	
Can assess cardiac function from echocardiogram videos, this assessment has been reported to be as accurate as human interpreter or even better than it [71]	
Automatic segmentation of the right ventricle from cardiac MRI using a learning-based approach [75]:	
Can be adequately utilized for automatic segmentation of the RV	Poor performance in patients with irregular RV shape,
	such as congenital heart defects
Performs better than techniques employed in MICCAI 2012 challenge, saves time, and is more accurate	Lack of adequate amount of data for training and validation

Table 5. Continued.

DIAGNOSIS OF HEART FAILURE CardioMEMS^{TM}:	
Automated segmentation of the left ventricle in cine cardiac MRI using neural network regression [125]:	
Performance indicates strong potential for utility in clinical practice	Model relies on assumptions which can fail to give accurate results, there was no reference data for few aspects of evaluation
Comparatively better results and accuracy than semi-automated approach	
The algorithm as a whole is insensitive to interslice changes because of patient movement between slice acquisitions	
Machine learning of three-dimensional right ventricular motion [13]:	
It can predict outcome in Pulmonary hypertensive patients	Not applicable in all groups
It is feasible, accurate, and reproducible	Uncertainty in displacement estimation due to uncertainty in end-diastolic and end-systolic segmentation
It is better in evaluating prognosis when compared with conventional parameters	
It can assess RV systolic function. It can help clinicians in determining physiology that underlie RV failure	
Automatic coronary artery calcium scoring in cardiac CT angiography using paired convolutional NN [126]:	
It reduces false positive and interobserver variability	
It can identify and quantify coronary artery calcification	
Automated Agatston score computation in non-ECG gated CT scans using deep learning [127]:	
It has good patient stratification	
It doesn't require a data set of explained calcifications, yet require just the CT scan input and the calculated Agatston score	
It is simpler than state-of-the-art detection networks	
SMARTool [128]:	
Can comprehensively assess risk profile for CAD and DSS	
It can estimate smartFFR index and site prediction for plaque growth	

Abbreviations: ECG, electrocardiogram; AI, artificial intelligence; CHF, congestive heart failure; CD, cardiac disease; BP ANN, back propagation-artificial neural network; HMM, hidden markov model; AL-CDSS, Artificial Intelligence-Clinical Decision Support System, PM, prediction model; DLM, deep learning model; HFpEF, heart failure with preserved ejection fraction; RRS, rapid response system; CRT, cardiac resynchronization therapy; DEWS, deep learning based early warning system; CAD, coronary artery disease; HF, heart failure; HFrEF, heart failure with reduced ejection fraction; IoT, internet of things; CT, computerized tomography; LV, left ventricle; LAV, Left atrial volume; LVEDV, left ventricular end diastolic volume; LVESV, left ventricular end systolic volume; LVEF, left ventricular ejection fraction; STE, speckled tracking electrocardiographic; RV, right ventricle; MRI, magnetic resonance imaging.

of revolutionizing accurate diagnosis and prediction of decompensation and mortality of HF patients by acting as a tool of assistance. In the post COVID-19 pandemic era where healthcare systems will be overburdened with HF related hospitalizations, the specialists treating HF patients should make efforts to train themselves in incorporating AI so practice of an AI-dependent medicine can be made more efficient and provide accurate diagnosis in a short span of time.

Author contributions

FY—Conception of the study, drafting, editing, reviewing, and final approval of the study to be submitted. SMIS—Help in the design of the study, drafting, editing, reviewing, and final approval of the study to be submitted. AN—Drafting, editing, and final approval of the study to be submitted. SMSU—Drafting, editing, and final approval of the study to be submitted. AJ—Drafting, editing, and final approval of the study to be submitted. SK—Drafting, editing, and final approval of the study to be submitted. SAS—Drafting, editing, and final approval of the study to be submitted. PK—Drafting, editing, and final approval of the study to be submitted. ShS—Drafting, editing, and final approval of the study to be submitted. SAH—Drafting, editing, and final approval of the study to be submitted. CD—Drafting, editing, and final approval of the study to be submitted. ASC—Drafting, editing, and final approval of the study to be submitted. AM—Critical revision of the manuscript, editing, reviewing, and final approval of the study to be submitted. SC—Critical revision of the manuscript, editing, reviewing, and final approval of the study to be submitted. HML—Critical revision of the manuscript, editing, reviewing, and final approval of the study to be submitted.

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