



Transforming Heart Failure Care Through AI: Advances and Future Directions

Sunil Junapudi,¹ Maseer Khan,² Syam Sundar Junapudi,³ Malavika Maduri,⁴ Tapasya Pamu,⁴ Kondati Pranathi,⁴ Sonia Arora,⁵ Shivani Chopra,⁶ Hitesh Chopra⁷

Abstract

Heart failure (HF) is a condition in which the heart cannot adequately pump enough blood to the body to meet its needs. Typically, this is due to a physical or functional problem with the heart. Although the traditional diagnostic and treatment options for HF have been improved upon, the growing numbers of individuals with HF (primarily due to cardiovascular diseases, hypertension and myocardial disorders) necessitate more specific, timely and personalised approaches to managing patients with HF. Artificial intelligence (AI), specifically machine learning (ML) and deep learning (DL), will have a significant impact on the future of cardiac care. AI has demonstrated increased accuracy for HF diagnosis, risk prediction, tailored therapies and rapid decision-making in clinical practice. The review will first provide an overview of the traditional methods for HF diagnostics and then compare them to the AI-based methods discussed later in the review. As shown in the review, AI generally offers a more accurate prediction of HF and allows for more frequent assessments. Traditionally, HF diagnostic methods rely on established guidelines and decision trees. In contrast, AI-based diagnostic methods utilise large amounts of complex input data including electronic health records (EHRs), electrocardiogram (ECG), echocardiogram images, CT/MRI scan results and laboratory test markers. These complex inputs allow AI to detect HF earlier than traditional methods, to better predict the risk associated with HF and to support development of individualised patient care plans. The article includes both a comparative analysis of HF diagnostics using traditional methods versus AI-based methods and examples of various smart implantable devices, vascular/structural heart interventions, rhythm-specific treatments and circulatory assistive devices to demonstrate the positive contributions of automated systems to higher recovery rates and reduced clinical burdens. Therefore, AI could represent a revolutionary new paradigm for managing HF, allowing clinicians to detect HF earlier and more accurately classify the type of HF, as well as select treatments based on evidence. With continued advancements in AI technology, combined with greater availability of real-world clinical patient data, it is likely that the delivery of HF care will undergo a significant transformation over the course of the next few decades.

Key words: Heart failure; Artificial intelligence; Machine learning; Deep learning; Cardiovascular diseases; Diagnosis; Risk; Echocardiography.

1. Department of Pharmaceutical Chemistry, Geethanjali College of Pharmacy, Cheeryal, Keesara, Medchal District, Telangana, India.
2. Epidemiology Program, Department of Public Health, College of Nursing and Health Sciences, Jazan University, Jazan, Kingdom of Saudi Arabia.
3. Department of Community Medicine, Government Medical College Suryapet, Telangana, India.
4. Department of Pharmacy, Geethanjali College of Pharmacy, Cheeryal, Keesara, Medchal District, Telangana, India.
5. Chandigarh College of Pharmacy, Chandigarh Group of colleges, Landran, Punjab, India.
6. Department of Biosciences, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India.
7. Centre for Research Impact and Outcome, Chitkara College of Pharmacy, Chitkara University, Rajpura, Punjab, India.

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Corresponding authors:

SUNIL JUNAPUDI
E: suniljunapudi@gmail.com

HITESH CHOPRA
E: chopraontheride@gmail.com

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Introduction

Heart failure (HF) or congestive heart failure (CHF), is a medical condition where the heart's pumping capacity fails to provide enough blood to the body to meet its metabolic needs, resulting from structural damage or dysfunction to the heart, or a combination of both. Cardiovascular disease is an ever-changing condition, so the need for timely, rapid and data driven diagnostic help is growing. Artificial intelligence (AI) helps meet this need because it can quickly analyse a vast amount of different information including electronic health records (EHRs), bio-signals and high-resolution images, among others. Cardiovascular disease (CVD) has many different manifestations and AI and machine learning (ML) will be helpful in evaluating disease risk, tracking disease progression, personalising therapy and developing new treatments.

The use of deep learning (DL) models on multiple types of cardiovascular imaging, including echocardiograms, coronary angiography, cardiac MRIs and electrocardiogram (ECG) images has shown improved diagnostic capabilities. A few examples of how DL models have been used to improve diagnostic capabilities include identifying HF in a patient, predicting a sudden cardiac death, detecting arrhythmias automatically and providing a detailed description of valvular lesions. One of the best examples of how DL model-based ECG analysis can detect subtle characteristics that may not be identifiable by human observers is its ability to identify the presence of paroxysmal supraventricular tachycardia (PSVT), which is a type of arrhythmia that can occur at any time and has abrupt onset and episodes of occurrence.¹ Overall, these examples illustrate a larger trend that is occurring; AI and ML are no longer experimental concepts but practical, clinically applicable tools to aid in diagnosing, phenotyping and longitudinally managing patients with HF.

Obstructive coronary artery disease remains the most common cause of decreased coronary perfusion leading to HF,² however other factors can contribute to HF. Identification of the root cause of HF is essential in order to determine both the appropriate diagnostic testing processes and treatment options for the patient as well as their long-term care plan. There are two main categories of HF drivers: intrinsic cardiac issues, such as myocardial ischemia or infection, valvular

heart disease, congenital abnormalities, cardiomyopathies and altered myocardial or extracellular matrix formation and systemic issues that continually increase the workload of the heart. In general, these two categories of HF drivers coexist in the normal clinical setting. For example, ischemic heart disease, chronic obstructive pulmonary disease (COPD), hypertensive heart disease and rheumatic heart disease account for approximately two thirds of all cases of HF globally; however, the prevalence of each of these conditions varies geographically³ and for example high income countries tend to see a much higher incidence of HF due to ischemic and COPD, whereas low and middle income countries tend to have a much higher incidence of HF due to hypertension, cardiomyopathy, rheumatic heart disease and myocarditis.

Diagnosis before the advent of AI

Traditionally, the evaluation of HF has been based upon a combination of clinical assessment, laboratory testing and cardiac imaging. The clinician begins evaluating HF at the bedside by assessing for typical symptoms and signs associated with impaired cardiac function. Laboratory testing that provides additional information regarding systemic status includes a complete blood cell count, urinalysis, an extended metabolic panel. The extended metabolic panel will include serum electrolytes (calcium, magnesium); renal function markers (BUN, creatinine); blood glucose; fasting lipid profile; liver enzymes; and thyroid stimulating hormone, each of which can impact either the pathophysiology of HF or therapeutic options for the management of HF.

Specific cardiac biomarkers are important when there is suspicion for HF. B-type natriuretic peptide (BNP) and its inactive pro-peptide fragment, N-terminal prohormone of BNP (NT-proBNP), are central to determining if HF is present because BNP and NT-proBNP levels are directly related to the degree of myocardial wall stress and ventricular filling pressure and correlate with the degree of HF. Additionally, according to the National Academy of Clinical Biochemistry, the ideal

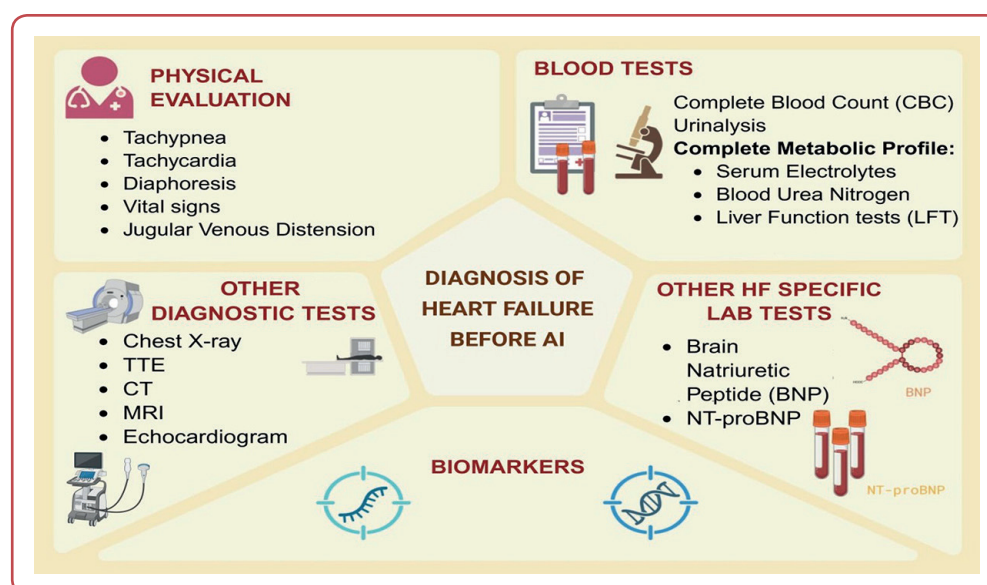


Figure 1: The evaluation for heart failure (HF) is performed using various parameters

TTE: transthoracic echocardiogram; CT: computed tomography; MRI: magnetic resonance imaging;

HF biomarker should help determine the possible underlying cause(s) of HF, help support or refute the initial clinical diagnosis of HF and provide prognostic information regarding the likelihood of future adverse clinical events.⁴

Imaging continues to be an essential component of the evaluation of HF. A chest X-ray can quickly assess cardiac size and pulmonary congestion. Transthoracic echocardiography (TTE), usually performed in conjunction with Doppler assessment, is the recommended first line of imaging for patients who have new or unexplained HF symptoms. TTE permits an assessment of the left ventricular size, left ventricular systolic and diastolic function and the morphology and function of all four heart valves. Additional imaging modalities such as cardiac CT or MRI may be used to obtain high resolution, multi-planar images of cardiac structures and tissues and thus complement echocardiographic findings.

Although the diagnostic tools mentioned above provide a comprehensive framework for diagnosing HF, most traditional risk prediction models do not perform well for HF. Traditional models can be limited in their ability to process complex, high-dimensional data sets and they are also highly susceptible to missing data and inconsistent recording of variables in daily clinical practice. ML methods, however, are capable of handling large and complex data sets, can identify relevant patterns in data even when it is incomplete and often outperform traditional statistical models in the prediction of outcomes for HF.⁵

Therefore, AI-based systems have great potential for supporting healthcare providers in the contemporary care of patients with HF. These systems may assist healthcare providers in recognising subtle, early signals for worsening HF, in identifying patients at increased risk for HF and other cardiovascular complications, in individualising therapy to a patient's unique characteristics and in providing accurate predictions of clinical outcomes for HF. As opposed to traditional statistical approaches that are based on specific assumptions about parameters, ML does not have these restrictions; thus, it can provide a high degree of reliability in many real-world situations where the data collected will be typically incomplete or imperfect as well as with other types of errors. As shown in Figure 1, there are several different HF diagnostic categories that were used to evaluate HF (and) therefore illustrate the complexity of evaluating HF.

Classification of HF phenotypes and treatments

There are four main phenotypic classifications for HF based on left ventricular ejection fraction (LVEF). These classifications are based on how much blood is pumped out of the left ventricle with each heartbeat. They include:

1. Heart failure with reduced ejection fraction (HFrEF)

2. Heart failure with mildly reduced ejection fraction (HFmrEF)
3. Heart failure with preserved ejection fraction (HFpEF)
4. Heart failure with improved ejection fraction (HFimpEF)

In regular practice, the classification of HFpEF is defined by an LVEF of $> 50\%$. The LVEF represents how well the left ventricle functions. An LVEF of $< 40\%$ classifies the patient as HFrEF, representing a substantial decrease in systolic pumping ability. A patient's LVEF value that falls between 40% and 49% identifies them as having HFmrEF; a transitional or intermediate form of HF that has been studied in depth regarding its biology and what treatments are most appropriate for these patients. The definition of HFimpEF includes patients that had a previous LVEF of $\leq 40\%$ but have now achieved an absolute increase of at least 10 percentage points in their LVEF. The majority of these patients will be able to partially restore some level of systolic function through the use of guideline-directed medical therapy (GDMT), cardiac resynchronisation therapy (CRT), or device-based interventions.⁶

Approach based on observable traits

The trait-based method for describing HF identifies clinically relevant and biological traits to further define HF by focusing on specific clinical and biological traits in addition to simple LVEF numbers. The aim is to create HF patient groups based on common clinical features or disease mechanisms such as common clinical manifestations, common comorbidities and common disease mechanisms; this will provide a better rationale for developing a treatment plan that addresses the unique needs of each group.

There are multiple mechanisms that contribute to the progression of HFpEF; these include low-grade chronic inflammation, coronary microvascular dysfunction, an increase in the stiffness of the myocardium and changes in titin phosphorylation. These mechanisms occur throughout all aspects of the heterogeneous spectrum of HFpEF and include patients with exertional dyspnoea, those who are obese, those who have metabolic syndrome, diabetes, atrial fibrillation and many others. Identifying the different trait clusters may allow clinicians to identify different groups of HFpEF patients with similar risks and responses to therapy and to develop targeted treatments rather than "one size fits all" strategies.⁷

Diuretics

Symptomatic treatment with diuretics remains one of the primary therapies in HFpEF. Diuretics cause a reduction in intravascular volume by causing natriuresis and thus a reduction in the left ventricular preload leading to a reduction in pulmonary venous and arterial pressures, which will decrease the workload of the right ventricle. Diuretics have their greatest potential for improving symptoms of congestive HF (dyspnoea, orthopnoea, peripheral oedema) by decreasing the left ventricular preload and therefore, the pulmonary capillary wedge pressure. However, due to the potential for diuretics to significantly lower blood pressure and potentially lead to impaired cardiac output and reduced renal perfusion due to decreased effective circulating volume, the use of diuretics requires careful titration of dose. Patients with HFpEF may have underlying renal microvascular disease and excessive diuresis could further exacerbate renal dysfunction, even to the point of precipitating acute kidney injury.

Therefore, the use of diuretics in patients with HFpEF should be tailored to the needs of each individual patient, with the goal of providing symptom relief from congestive HF while maintaining adequate haemodynamics and electrolyte balance. Hence it will be required to assess regularly for the patient's body weight, blood pressure, renal function and serum electrolyte levels, in order to achieve a balance, which will optimise both the relief of symptoms and the prevention of potential adverse effects from the excessive diuresis. To accomplish this goal the ideal method to do so will be to titrate the dose of the diuretic on the basis of the patient's daily weight loss, blood pressure response and the level of clinical improvement of the patient.

More recently studies have demonstrated that the efficacy of diuretic treatment in patients with HFpEF, can be enhanced by the use of devices that measure the cardiac pressure. There appears to be significant evidence that many patients diagnosed with stable HFpEF are experiencing elevated diastolic pressures in the left ventricle. These elevated diastolic pressures are associated with a poor prognosis and, as such, represent a significant risk factor for the development of unstable forms of HF. Furthermore, the progression of stable HF to an unstable form of HF typically involves an increase in diastolic pressures in the left ventricle over time, often taking weeks. Studies using data from implanted sensors have

shown a significant reduction in mortality and morbidity related to cardiovascular problems, including reductions in hospitalisations due to fluid overload in patients with HFpEF treated with diuretics.⁸

Caloric restriction

Since extra body fat can increase inflammation while weakening heart, blood vessel, kidney, or muscle performance, losing weight is often advised for many people with HFpEF. In a study by Kitzman et al, cutting calories over 20 weeks worked well - and safely - for older adults who were overweight and had HFpEF, boosting their symptom reports, exercise capacity (measured as VO_2), along with overall daily functioning. Dietary changes led to larger gains in quality of life compared to physical activity by itself. Moreover, pairing lower calorie intake with steady aerobic training brought further advantages - boosting peak VO_2 significantly by 2.5 mL/kg/min, matching or exceeding drug-related improvements observed in HFpEF cases. Such enhancement aligned with positive shifts across several separate performance indicators: oxygen reserve capacity, duration of exertion, intensity tolerance, walking distance over six minutes and strength output in legs. Gains in maximal oxygen use linked closely to loss of body fat, growth in muscle tissue, improved ratio of thigh muscle versus surrounding fatty deposits, along with lowered markers tied to chronic inflammation, suggesting that widespread immune activation plays a key part in limiting physical function for individuals with HFpEF.⁹

Statins

The involvement of widespread inflammation in HFpEF suggests statins may help. Because they affect vascular oxidative processes, these drugs enhance nitric oxide levels in vessel walls regardless of lipid changes. Endomyocardial biopsies reveal lower nitrotyrosine in heart tissue of HFpEF individuals on statins - alongside higher PKC activation. These samples also show smaller cardiac muscle cells, while baseline cell stiffness appears diminished. Data from observational work indicate fewer cases of atrial fibrillation among such patients using these drugs.¹⁰

Inorganic nitrite/nitrate

In patients with HFpEF, the myocardium often operates under a state of reduced nitric oxide (NO) availability and diminished cGMP signalling.

Much of this pathophysiology arises from dysfunctional endothelial signalling within the microvasculature. To compensate for the resulting NO deficit and reduce vascular load, investigators have evaluated organic NO-donating therapies. A study conducted by Redfield et al., however, challenged the approach used by these investigators: isosorbide mononitrate did not improve physical performance; it reduced total daily activity.¹¹ The results of this investigation have serious implications for the use of nitric oxide donors in patients with HFpEF. They suggest that excessive drops in blood pressure, diminished left ventricular filling and subsequent declines in stroke volume, as well as development of "pharmacologic tolerance" (ie, diminished responsiveness to the drug) may limit the effectiveness of conventional nitrates in treating patients with HFpEF. In addition, prolonged exposure to NO can cause decreased renal perfusion and increased sodium retention, both of which can lead to what has been termed "pseudo-tolerance." In addition, organic nitrates may further aggravate endothelial dysfunction an established driver of HFpEF pathogenesis thereby potentially worsening the very condition they are intended to treat.

ML in HF classification and treatment

ML shows strong potential for improving how we categorise HF and adjust therapies. A study of 397 outpatients with preserved ejection fraction used ML models fed by electronic records to uncover new subtypes - drawing from symptoms, echo results, ECGs, pressure measurements during procedures, along with patient follow-up data. An alternative unsupervised ML method examined 1,693 admitted HF individuals spanning various LVEF levels - grouping them into six clusters according to frequent coexisting conditions like coronary issues, valve disorders, irregular heartbeat, lung disease, breathing interruptions during sleep, or few accompanying illnesses.¹² In contrast to using ejection fraction by itself, this strategy improved prediction of cardiac-related complications.

Ahmad et al¹³ applied ML to data from 44,886 individuals in the Swedish HF Register, uncovering four distinct clusters linked to how they responded to therapy. Because of this classifica-

tion, chances of surviving twelve months went up while guiding care more precisely toward established treatments. By using such models, clinicians can spot those likely to gain most - adjusting when drugs are given, their amounts, or tailoring interventions rooted in proof.

ML may help choose the right device treatments. About 30 % of HF cases don't benefit from cardiac resynchronisation therapy. A post hoc analysis of the MADIT-CRT trial demonstrated that algorithm-based stratification could separate patients into four distinct clusters, thereby improving the ability to predict treatment response. Using data driven phenotyping in patients with implantable cardioverter-defibrillator (ICD) devices identified clinical patient groups that may be better managed by an individual approach than a one-size-fits-all strategy. Shakibfar et al¹⁴ demonstrated ML models trained solely on the daily diagnostic ICD reports can identify short term risk for electrical storm episodes; as well as DL approaches to identify patients that would benefit from subcutaneous ICD placement.

Forecasting evaluation of ML algorithms

In addition to other tools in the health-care industry, ML technology offers many advanced techniques for detecting, classifying and predicting a variety of diseases. Many recent studies have focused on integrating large amounts of clinical data into machine-learning-based models to predict the likelihood of a number of different conditions (ie cardiovascular events or congestive HF). These studies show how ML models may help identify potential diagnoses at an earlier stage than traditional medical diagnostic methods, allow clinicians to provide patients with personalised risk assessments and improve clinical decision making.

ML is a subset of AI, which uses algorithms to "learn" from examples in order to develop predictive capabilities from data. Unlike the traditional rule-based approach of AI, ML algorithms adjust their internal parameters based on examples provided and therefore continually improve their predictive capability as additional data are provided. The most common ways to group ML algorithms include the format of the input data; supervised learning, in which the model learns from labelled data (where the correct output for each example is defined) and the model generates desired output (ie disease/no-disease); un-

supervised learning, in which the model discovers structure or grouping within unlabelled data. ML algorithms can also be grouped by the type of output produced by the algorithm; classification algorithms produce a categorical output (ie low-medium-high risk patients); regression algorithms produce a continuous output (ie predicted length of life, probability of future adverse event). The evaluation metrics for clinical forecasting models include accuracy, sensitivity, specificity and area under the receiver operating characteristic (ROC) curve; all of which provide assurance that the chosen algorithm will support quality patient care.

DL and artificial neural networks

DL is a cutting-edge area of ML that has been influenced by the manner in which humans process and integrate information. The basis for DL's neural networks are artificial neural networks (ANNs). ANNs are composed of multiple layers of interconnected nodes called neurons. These neurons use adjustable weights along with a mathematical function to apply their own weighting to inputted signals and then pass the output from each node forward through the network.

In DL neural networks, activation functions are used at each layer to manipulate the inputted signal as it propagates through the layers of the network. In this manner, each subsequent layer creates a representation of the inputted data that becomes increasingly abstract and informative. Compared to earlier types of neural networks (such as the single-layered perceptron), DL networks have significantly more layers and a much larger number of free parameters. Therefore, DL networks can learn subtle, non-linear relationships between input variables automatically with little to no need for manually selecting features.

Due to its layered structure, DL is well suited for the analysis of large amounts of complex and/or high dimensional data, ie, large amounts of medical imaging data, large amounts of physiological signals and large amounts of electronic health record data. Typically, the training of DL models occurs via iterative adjustment of the adjustable weights using back-propagation and gradient-based optimisation techniques to minimise the difference between predicted outcomes and actual outcomes. As a result of these advancements in design and training of DL models, well designed DL models can be extremely accurate

in identifying diseases, predicting outcomes and recognising patterns in a variety of clinical research and clinical applications.

ML for predicting heart conditions

Researchers in the area of cardiovascular medicine have demonstrated that recurrent neural networks (RNNs) are capable of modelling the progression of HF, using longitudinal data from EHRs. The research framework used by Goretti and colleagues,¹⁵ included three major groups of variables: (i) time dependent variables (eg, ejection fraction as a function of height, BNP as a function of NYHA Class, age as a function of blood pressure and heart rate as a function of prescribed dose of ACE inhibitors, beta blockers, diuretics); (ii) binary indicators (eg, ischaemic heart disease, hypertension, dyslipidaemia, normal vs abnormal heart rhythm, diabetes, chronic lung disease, nitrates); (iii) ordinal characteristics (eg drug-dose levels, patient adherence scores). A comparison of four model configurations was made, which included variations on the model configurations described by Zhao et al.¹⁶ The comparison included one variation where RNNs were substituted for 1-dimensional convolutional neural networks (1D-CNNs). Dropout layers were introduced to limit overfitting, long short-term memory (LSTM) units processed sequential inputs and fully connected layers handled non-sequential covariates.

Adler et al¹⁷ introduced MARKER-HF, an Ada-Boost-based decision tree model designed to predict mortality risk in patients with HF. Rather than relying on traditional biomarkers, the system uses eight routinely available clinical parameters: diastolic blood pressure, creatinine, blood urea nitrogen (BUN), haemoglobin, white blood cell count, platelet count, albumin and red cell distribution width. Compared with the commonly used marker NT-proBNP for HF, the Markers-HF biomarkers have shown consistent better discrimination in the identification of all possible subgroups of patients, therefore it could be a useful tool for clinical practice.

Golas and coworkers¹⁸ investigated six families of DL, including: deep neural networks, auto-encoders, restricted Boltzmann machine, RNN and convolutional neural networks (CNN) to predict the risk of early hospital readmission after discharge. The best performance in terms of predictive power was found among deep neural networks.

The authors proposed the deep unified network (DUN), which is based on the idea of using deep architecture (tall, multi-layered) with large, but shallow architecture. DUN allows to dynamically adjust the number of layers and the size of each layer depending on the complexity of the input data, thus reducing the problem of overfitting and alleviating vanishing gradients, leading to stable training and improved generalisability.

Nabrdalik and coworkers¹⁹ applied ML to identify cardiovascular risk factors in individuals with metabolic associated fatty liver disease (MAFLD). They used a combination of logistic regression and single variable filters and principal component analysis to select the best predictors. The performance of the model was mainly measured through ROC curves and area under the ROC curve (AUC).

Using similar approaches to those developed by Nabrdalik and coworkers,¹⁹ Ahn and coworkers²⁰ and Bhatt and coworkers²¹ evaluated some of the most popular ML algorithm to predict the risk of HF and related outcomes in hospitals, comparing them to clinicians' judgment. These authors also highlighted the potential of the use of data-driven tools in hospitals to help clinicians to better understand the risk of their patients and to guide them in selecting the appropriate strategy for the surveillance and for the early intervention.

Hasan and coworkers²² demonstrated the impact of different ways to select the variables used to build a model to predict cardiovascular outcomes. They analysed three types of feature selections: filter-based, wrapper-based and embedded, showing that the combination of the overlap between the selected variables in the previous approaches improves the performance of the classifier. XGBoost performed always better than ANNs, especially when they were used with wrapper-based feature subset.

These studies show that both classical ML and DL have great potential to predict HF and other cardiovascular events. Most of the time, architectures recurrent and convolutional and hybrid deep models outperform traditional statistical methods. Advances in feature selection, multi-modal data fusion and robust validation will continue to improve the predictive accuracy and will allow a personalised management of patients at cardiovascular risk.

AI in diagnostic devices

The majority of cardiovascular diseases do not present overt symptoms in the initial phase of disease development, thus complicating an accurate and timely diagnosis for clinicians. A delay or misinterpretation of diagnosis results in a delay in appropriately initiating treatment and leads to less efficient utilisation of health care resources and ultimately worse patient outcomes. As AI is being utilised as a supportive tool to aid in diagnostic decisions, the use of AI has become more common in various subspecialties of medical imaging. Recent advancements in AI have allowed for rapid progress in the field of radiology and other related disciplines, through the use of AI to assist in the evaluation of medical images, the identification of subtle abnormalities and the optimisation of clinician workflows.

With their capacity to recognise faint or complex patterns that would have gone unnoticed by even the most skilled physician, AI based systems will allow physicians to utilise AI as a supplemental component of their own expertise rather than replace it; As mentioned before AI has been utilised in cardiology, but tools are currently being developed and deployed within neurology, oncology and psychiatry, demonstrating its vast potential for use across various specialties. The integration of information from various imaging modalities and clinical data sources via AI will help to improve the accuracy of medical image interpretation, minimise the number of interpretative errors resulting from oversight and streamline clinical decision making. In summary, the AI-based diagnostic platform is a pathway toward earlier disease identification, higher diagnostic accuracy and better patient care for cardiovascular medicine.²³

AI in ECG

AI can provide a faster, more consistent and higher volume ECG interpretation than manual ECG interpretation. It allows clinicians to make more accurate diagnoses, to better identify patients at risk for future complications and to make more informed treatment choices. ML algorithms are able to detect small structural and functional changes in the heart that may not be visible during an initial evaluation. Early detection of HF using ML models can lead to prompt intervention and improve patient outcomes.

Hannun et al²⁴ developed a deep neural network model that was able to classify various types of cardiac arrhythmias from single-lead ECGs, similar to the classification ability of a trained cardiologist. The use of large databases of annotated ECG data has allowed CNN-based models to find hidden relationships between ECG signals and silent left ventricular dysfunction, subclinical atrial fibrillation and early myocardial hypertrophy. Some AI models are also able to determine a patient's demographic characteristics (eg age, gender), directly from the ECG signal, indicating that there is potentially more information contained within the ECG signal than was previously thought.

Natural language processing (NLP) further expands the capabilities of this field by relating ECG data to echocardiography reports and other clinical documentation; allowing the AI system to calculate LV function, estimate EF and create risk scores for adverse outcomes. This type of approach enables a clinician to more quickly evaluate the patient's condition and increases the reliability of their predictions regarding patient outcomes. Overall, NLP, along with ML and computer vision, creates a comprehensive platform for integrating all forms of clinical data and ultimately provides an additional resource for clinicians evaluating cardiovascular disease through ECG-based assessments.²⁵

AI in echocardiography

Although echocardiography can be used to evaluate heart structure and function, its value is limited because both the quality of images produced and their interpretation depend upon the operator's technical skills and the interpreter's knowledge. Consequently, while clinically interpretable echocardiograms are generated, many different versions exist, which vary primarily based on differing levels of image quality and/or varying degrees of expertise among readers. One way in which AI-based methods could help decrease this variability in the interpretation of echocardiograms would be to create and utilise a consistent method for analysing images and to automate image analysis in order to dramatically reduce the time and effort involved in performing such analyses.

In echocardiography, several applications currently exist for the use of modern AI-based technologies including the automatic identification

and classification of echocardiogram views, the automated segmentation of cardiac structures at high spatial resolution, the quantitative assessment of left ventricular function and regional contractility and the enhancement of the ability to identify and classify complex cardiomyopathies.

Zhang et al²⁶ reported on the application of a DL methodology to develop an AI-based system capable of accurately identifying 23 unique echocardiogram views, capable of accurately segmenting cardiac chambers and capable of distinguishing between structurally normal hearts and those with structural abnormalities. In addition to the capability to replicate the standard visual evaluations performed by human readers, AI-based systems offer the benefit of providing reproducible measurements of cardiac function and structure, thereby reducing the degree of variability associated with inter-reader and intra-reader comparisons.²⁷

The use of AI-enhanced echocardiography represents a vast expansion of the traditional role of echocardiography in image interpretation. With the inclusion of AI-enhanced echocardiography into a comprehensive evaluation of patients including clinical data (ie patient history and physical examination), laboratory data and longitudinal patient history, models can also be trained to differentiate between physiologic hypertrophy in athletes and pathologic hypertrophy (eg hypertrophic cardiomyopathy, HCM). Ultimately, the inclusion of patient-specific information with the imaging data will lead to enhanced confidence in diagnosis, a reduction in the time needed to interpret studies and a reduction in the need to manually measure parameters related to cardiac function, thus increasing the overall efficiency of the diagnostic process and enhancing the personalisation of cardiovascular care.

AI in cardiac CT and MRI

DL algorithms have improved the quality of cardiac CT images. The DL algorithms help reduce the amount of “noise” in low dose scans, correct for motion artifacts that occur when a patient is moving during an imaging exam and enhance the contrast to noise ratio of the images, all of which are improvements in the image reconstruction process.²³ This allows for shorter scan times using less radiation and contrast media, while maintaining or even improving diagnostic accuracy for coronary artery disease. From an interpretation standpoint, AI will automatically de-

tect coronary calcifications, measure the amount of plaque present, determine the type of plaque present (ie soft, hard) and support risk assessment and future monitoring.

Cardiac MRI is still considered the gold standard for evaluating chamber volumes, ventricular function, characteristics of myocardial tissue and visualising scars via late gadolinium enhancement. However, AI algorithms have enabled automatic segmentation of ventricular cavities and myocardial borders in Cardiac MRI to reduce the time needed for contouring and reduce inter-observer variability.²³ Additionally, ML models have been developed to enhance T1, T2 and T2* mapping sequences to speed up the acquisition of these sequences, enhance the quality of parametric maps and facilitate the detection of diffuse fibrosis, oedema and iron overload. Techniques are emerging that will allow non-contrast tissue characterisation, which would be beneficial for patients with kidney dysfunction or those who are contraindicated for gadolinium.²⁸

In addition to the analysis of individual modalities, AI has facilitated the integration of anatomical and functional data obtained from CT, MRI, nuclear imaging and echocardiography to assist in the pre-procedural planning for complex interventions including transcatheter valve replacement, left atrial appendage closure and ablation procedures.²⁸ The most prominent use for this method is the non-invasive estimation of fractional flow reserve (FFR) from coronary computed tomography angiography (CCTA), using AI to integrate the anatomy of coronary arteries and the haemodynamics involved in estimating the pressure drop through stenotic areas using computer models. The models have shown equal or greater accuracy than invasive FFR methods making it possible to evaluate the physiological effects of coronary lesions on patients without exposing them to the risks associated with catheter-based diagnostic procedures and manipulating pressure wires.²⁹

AI in percutaneous coronary intervention (PCI)

Although PCI continues to be the major treatment approach for ischaemic heart disease; the successful performance of the procedure, along with the patient’s long-term prognosis, are contingent upon an accurate determination of the lesion, an appropriate choice of medical devices and the clinician’s use of his/her clinical judgment at the

time of the procedure. AI is becoming increasingly integrated within each segment of the entire PCI pathway - identification of significant stenosis, prediction of procedural and post-procedure risks, etc. Enhanced ML based non-invasive fractional flow reserve (FFR) from CCTA enables clinicians to identify hemodynamic significance of lesions prior to entering the catheterisation laboratory - thus improving case selection and reducing the need for unnecessary invasive angiography.²³

Within the catheterisation laboratory, AI-enhanced quantitative coronary angiography (QCA) is capable of automatically outlining vessel borders, estimating the degree of stenosis, providing 3D images and standardising the analysis of lesions. In addition, during the performance of the procedure itself, AI systems are able to provide guidance in choosing the optimal angiographic views to utilise, determine the best route to enter the vessel, guide wire placement - particularly when dealing with complex anatomy, ie chronic total occlusions, or bifurcation lesions. The integration of AI with other intravascular imaging technologies (ie IVUS, OCT) enable automatic lumen/plaque segmentation, stent sizing and detection of malposition/under-expansion - all of which aid in the personalisation of device selection and in turn, will result in more accurate stent placement - ultimately resulting in lower rates of restenosis/stent thrombosis.³⁰

Finally, predictive models that combine clinical information, angiographic data and procedural variables, are able to predict the probability of complications occurring post-procedure, eg bleeding, contrast-induced nephropathy and target lesion failure. This type of risk stratification tool may impact the decision-making process regarding antiplatelet therapy, follow up imaging and secondary prevention strategies. With the ability to provide more accurate lesion characterisation and allow for individualised treatment planning, AI has the potential to improve the outcomes of interventional cardiologists performing PCI procedures and potentially shorten procedure times, reduce the amount of contrast used and reduce the radiation exposure for both patients and operators.³¹

AI in structural heart procedures

The use of structural heart interventions like transcatheter aortic valve replacement (TAVR),

transcatheter mitral valve repair (TMVR) is dependent upon very precise imaging and detailed pre-procedure planning. AI has enhanced all phases of this process for TAVR and TMVR case selection, device sizing, access route planning and risk prediction through the extraction of greater amounts of data from multimodal imaging than is possible through a physician's eyes alone.

When ML is applied to CT, echo and MRI datasets, they may automatically identify structures of the heart, measure annulus diameters and provide a suggestion of optimal prosthesis size, which should minimise differences between observers and reduce surprise at procedural times. In addition to providing automated measurements, AI may combine clinical and anatomic parameters to create personalised risk profiles that allow clinicians to make more objective decisions regarding whether a transcatheter or surgical approach would be better for a given patient.

In addition to static planning, AI allows for the creation of personalised three-dimensional models of the heart and "digital twins" of the heart. These models can be utilised to simulate valve deployment, predict potential paravalvular leaks and predict outflow tract obstructions prior to initiating the procedure. The mixed reality platforms (Microsoft HoloLens) will then display the reconstructions within the surgeon's line-of-sight in the Cath lab, allowing for real time spatial awareness and guidance during the procedure. Ultimately, through the reduction of the amount of time spent planning, improved spatial awareness and the standardisation of complex decisions, AI-enhanced workflows have the potential to improve the accuracy of procedures and ultimately, the outcome of patients treated with structural heart interventions; particularly in the least experienced of practitioners and in centres that treat lower volumes of patients.³²

AI in electrophysiology and ablation procedures

Historically, electrophysiology has utilised advanced mapping systems and signal processing techniques to determine where an arrhythmogenic substrate exists. AI now provides another level of analysis through integrating multiple layers of information from Surface ECGs; intracardiac electrograms; advanced imaging and clinical data into single predictive models. Modern AI Tools can: create personalised virtual heart models that sim-

ulate various ablation strategies prior to entering the lab; develop predictive models for determining the likelihood of recurrence of atrial fibrillation post-ablation based on rhythm history; substrate characteristics; procedural parameters.

In the electrophysiology laboratory, AI-driven mapping systems can identify key conduction pathways; guide catheter placement; suggest real time lesion sets, which may shorten procedure duration and improve long term rhythm control. In addition, AI-assisted robotic ablation platforms improve catheter stability and contact force that allow for more accurate lesion delivery with a consistent application of energy. By using optimised navigation paths and smarter imaging protocols, fluoroscopy time will be reduced thereby decreasing radiation exposure for patients and staff. As such, these advancements are enabling changes in how we treat rhythms: ablation is being made not only more precise and efficient, but also more accessible; decision-support systems are making it possible for less-experienced operators to confidently and safely perform complex procedures.

AI in mechanical circulatory support (MCS)

AI is used to help doctors make better decisions about their patient's care; and it can be a predictive tool that helps identify potential risk areas; it also has been shown to enhance the effectiveness of heart-assisting devices (such as LVADs, RVADs) and emergency treatments for sudden cardiac arrest. Instead of manual evaluations by doctors, AI can evaluate how well the heart chambers are functioning and predict when there may be an issue with the right side of the heart and assist doctors in developing a plan to wean off a heart-assistance device over time. AI can improve the quality of images taken during medical imaging tests such as MRI and CT scans by reducing variability in measurement and therefore reducing variability in doctor's interpretations of those images, which will ultimately lead to faster and more effective diagnosis and treatment of a patient. A breakdown of AI techniques used to identify as well as categorise HF can be found in Table 1.

Table 1: Artificial intelligence (AI) methods for heart failure (HF) detection and classification

Objective/ focus	AI method	Features	Output	Limitations	Author
Detection of HF and its severity	Dual SVM scoring model	Clinical tests: blood, HRV, echo, ECG, chest X-ray, 6MWD, physical tests	Classification: healthy, HF-prone, HF	Requires dual model calibration; rigid thresholds	Yang et al, [33]
Detect the presence of HF	Feedforward neural network	Gender, age, BP, smoking habit	Feasibility shown; limited by sample size	Small sample size limits generalisation	Ghareh Chopogh et al, [34]
Detect CHF vs dyspnoea using Pro-BNP	Rough sets + logistic regression + decision tree	Lab findings	Reduced feature set to classify CHF	High dimensionality, risk of overfitting	Son et al, [35]
Early detection of HF (before diagnosis)	SVM, boosting, logistic regression, decision tree (C4.5)	Risk scoring via clinical features	Predict five HF risk levels	Lack of transparency	Wu et al, [36]; Aljaaf et al, [37]
Detect CHF using long-term ECG	Random forests, SVM, ANN, k-NN	Raw ECG features using the Burg method	Performance measured via sensitivity, specificity, ROC	Set-specific performance; computationally intensive	Masetic et al, [38]
Computer-assisted CHF diagnosis	Least squares SVM (LS-SVM)	Heart sound and cardiac reserve features	Superior to ANN and HMM for CHF detection	Dependent on heart sound quality, complex features	Zheng et al, [39]
HF severity estimation	Neuro-fuzzy expert system + feedforward NN	Signs/symptom MS: chest pain, dyspnoea, oedema, BP, HR, echo	DSFV score stratification into HF severity levels	Complex neural architecture; subjective	Akinyokun et al, [40]

Remote HF severity monitoring	CART using HRV features	Short-term HRV from ECG	NYHA Class I/II (Mild) vs III (Severe)	Limited by HRV only; excludes multimodal data	Pecchia et al, [41]
HF severity classification (long-term HRV)	CART, C4.5, random forest with/without SMOTE	Long-term HRV from ECG	Low risk (NYHA I/II) vs high risk (NYHA III/IV)	Requires large, balanced datasets	Melillo et al, [42]
Severity estimation using clustering + SVM	Clustering combined with SVM	Cluster features + Charlson score	Low vs high risk prediction	Doesn't use physiological data	Sideris et al, [43]
HF phenotype identification	Unsupervised clustering + latent class analysis	Obesity, diabetes, CAD, CKD	HF phenotypes based on comorbidities	Information loss via binning	Katz et al, [44]
Echocardiographic clustering for prognosis	Automated hierarchical clustering	Diastolic & chronotropic reserve (echo variables)	Subgroup identification with poor prognosis	Doesn't handle categorical variables effectively	Przewlock Kosmala et al, [45]
HFpEF phenotyping	Agglomerative hierarchical + penalised model-based clustering	CKD, AF, NT-proBNP, diabetes	Three HFpEF phenotypes with risk stratification	Limited to continuous variables	Shah et al, [46]

SVM: support vector machines, HF: heart failure, CHF: congestive heart failure, ANN: artificial neural networks, ROC: receiver operating characteristic, AUC: area under curve, LS-SVM: least squares support vector machine, k-NN: k-nearest neighbour; ECG: electrocardiogram, BP: blood pressure; CKD: chronic kidney disease; AF: atrial fibrillation; CAD: coronary artery disease; HFpEF: heart failure with preserved ejection fraction;

Applications of AI techniques in the diagnosis of HF

AI has changed how doctors estimate heart disease risks - also helping spot types of HF, create new blood pressure drugs, while refining care plans. Figuring out if someone has HF stays difficult, not just for experts, due to its nature: it stems from issues in heart structure or function, instead of one clear illness.

Take leg swelling as an example. Many people immediately associate it with right-sided HF, yet the story is rarely that simple. Fluid buildup in the legs can just as easily arise from weakened veins, long-standing kidney disease, or even medications that cause water retention. Since many cardiovascular and non-cardiovascular disorders show similar clinical signs and symptoms with HF, diagnosing true HF vs other potential causes is a common challenge faced by physicians and healthcare professionals in a variety of environments (ie primary care, high volume clinics). The challenges of identifying HF have been further complicated by the increasing number of new studies, expanding treatment options and increasing time constraints to diagnose HF within the primary care and high-volume clinic environment. In the setting described above, AI is developing into a clinically useful tool. AI is capable of identifying complex and subtle patterns in clinical, imaging and biomarker information, which

enables it to identify patients that are likely to develop HF earlier than would be possible through other means. Beyond providing risk stratification, AI can assist in reducing the time to make decisions regarding diagnosis, improve diagnostic accuracy and provide tailored management options for each patient. When implemented appropriately, AI has the capability to diminish the amount of ambiguity associated with a diagnosis of HF, enable physicians to deal with both typical and atypical cases as well as those involving multiple comorbidities and ensure that high risk patients receive appropriate interventions in a timely manner.⁸ Applications of AI to detect cardiac dysfunction and related conditions are currently being developed and continually refined as shown in Figure 2.

Yang et al³³ created a scoring model to detect HF and classify the severity of it using two separate Support Vector Machine (SVM) models. One SVM identifies whether a patient has HF or not, the second SVM takes the non-HF group and stratifies them into healthy individuals and those who are at risk of developing HF due to their profile scores.⁴⁷

Ghareh Chopogh et al³⁴ employed Neural Networks in a pilot study of only 40 participants. Although there were a small number of subjects, they were able to differentiate between HF pa-

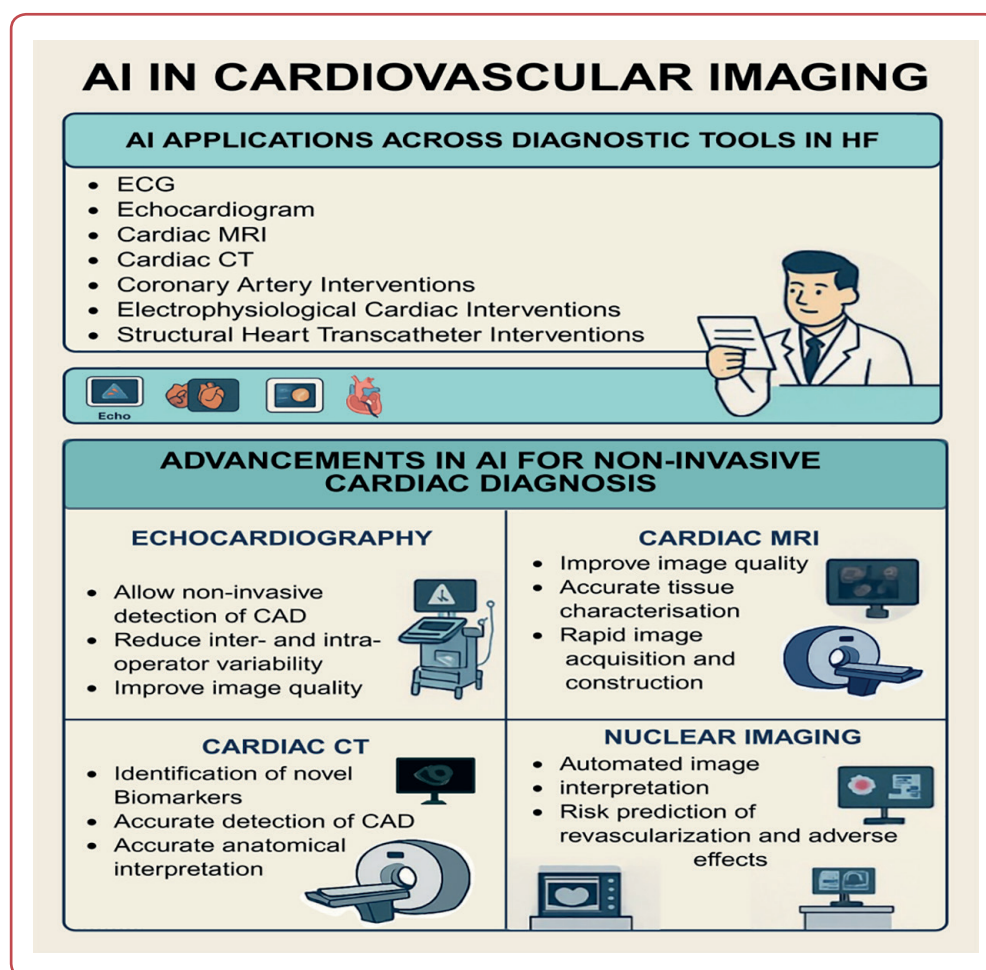


Figure 2: Artificial intelligence (AI) in cardiac diagnoses is advancing and being utilised in diagnosis
 CAD: coronary artery disease; CT: computed tomography; MRI: magnetic resonance imaging; ECG: electrocardiogram;

tients and non-HF patients. Although they were able to demonstrate the potential for AI-based systems to diagnose HF, the small number of participants demonstrates a primary limitation of AI-based models – they typically do poorly when scaled to larger, more diverse populations.

Son et al³⁵ developed a method to use a wealth of clinical data, starting with 72 variables to determine if patients had congestive HF or another cause for their symptoms of dyspnoea. After applying a combination of rough set theory (RST) and logistic regression (LR) to determine the most relevant variables to include in a decision tree classifier for HF diagnosis, they determined that Pro-BNP was a strong indicator for HF and that systematically selecting the most informative variables could improve clinical decision making.

Masetic et al³⁸ employed random forests and long-term ECGs to create an approach that performs better than most ML approaches (ANN,

SVM, C4.5, K-NN), for the purpose of identifying HF. The approach demonstrated excellent sensitivity and specificity and highlighted how ensemble methods can successfully detect the small differences in ECG of patients diagnosed with HF.

ML is becoming increasingly utilised to forecast future illness and, specifically, the progression of HF. Wu et al³⁶ and Aljaaf et al³⁷ showed that predictive models can identify individuals who will progress to HF up to 6 months prior to receiving a formal clinical diagnosis, thus allowing for earlier intervention and continued assessment of those at risk for HF. Zheng et al³⁹ approached this problem differently by developing a digital diagnostic system that utilises LS-SVM with features derived from cardiac function and heart sounds, thereby providing a non-invasive mechanism to diagnose congestive HF and demonstrating the growing significance of acoustic biomarkers for the evaluation of HF.

In contrast, some of the more recent research has

concentrated on employing unsupervised learning techniques to distinguish the clinical and biological heterogeneity found within HF populations, especially in HFpEF. Shah et al⁴⁶ employed clustering to determine three reproducible HFpEF phenotypes that had distinct clinical and prognostic profiles: a high-risk phenotype that was defined by increased incidence of CKD, AF and NT-proBNP; and an intermediate-risk phenotype that included a higher prevalence of diabetes. Similarly, Przewlocka-Kosmala et al⁴⁵ utilised hierarchical clustering to separate HFpEF patients based on echocardiographic indices and demonstrated a sub-population of HFpEF patients characterised by impaired diastolic function and reduced chronotropic reserve, both of which are associated with poor prognosis. However, the use of solely quantitative variables likely reduced the resolution of the resultant clusters.

Katz et al⁴⁴ sought to address this limitation using latent class analysis (LCA) which allows for simultaneous processing of both categorical and continuous input variables and demonstrated that HF phenotypes are enriched for obesity, diabetes, CAD and CKD. As LCA typically requires the grouping of continuous measures into discrete categories, clinically relevant variability within continuous measures may be lost.

Sideris et al⁴³ expanded the boundaries of past studies by determining latent structure from electronic health records. They categorised related diagnosis codes into clinically relevant categories and then used these categories as inputs to an SVM classifier. By incorporating the Charlson comorbidity index into these category inputs,

Sideris et al⁴³ were able to improve the accuracy of HF staging predictions and show the potential to utilise structured patterns of EHR data to enhance risk stratification.

Akinyokun et al⁴⁰ developed a hybrid approach combining neural networks with fuzzy logic. Akinyokun et al's⁴⁰ model classified HF into five stages of severity (no functional limitations to end stage HF) using only six key patient variables and demonstrated that carefully selected, low-dimension variable sets can provide clinically useful classification.

Applications for remote monitoring are also gaining attention. Pecchia et al⁴¹ applied CART decision tree to short ECG-derived HRV segments to differentiate between patients with mild-to-moderate HF (NYHA I-II) and more severe manifestations of the disease (NYHA III). Building upon this work, Melillo et al⁴² evaluated longer Holter recordings and compared several classifiers (Random Forest and C4.5), each with and without SMOTE-based class balancing. Melillo et al's⁴² models were consistently capable of separating patients into lower-risk (NYHA I/II) and higher-risk (NYHA III/IV) groups and demonstrate the potential for wearable-based data to support telemedicine and remote assessments of HF. Together, these studies demonstrate the rapidly evolving role of AI in managing HF, from early detection and phenotypic stratification to continuous and real-time monitoring. However, there are still many challenges remaining in terms of the quality of the data, the ability to interpret models and the large-scale clinical implementation of next-generation AI-enabled HF solutions (Table 2).

Table 2: Artificial intelligence (AI) applications across diagnostic tools in heart failure (HF)

Diagnostic tool	Role	AI application	Algorithm/techniques	Advancements
ECG	Non-invasive diagnostic evaluation of cardiovascular pathology.	Improve ECG interpretation, stratification, prognostication and detect early HF indicators.	DNN, CNN, NLP pairing with echocardiogram.	High accuracy arrhythmia diagnosis, early HF detection, cardio-logist-level performance.
Echocardiograms	Screening, characterisation and diagnosis of cardiomyopathy.	View recognition, cavity segmentation, functional assessment, disease diagnosis.	CNN (Zhang et al [26]), ML differentiation of HCM vs athlete's heart.	23-view recognition, accurate chamber volume measurement and disease discrimination.

Cardiac MRI	Non-invasive quantification of ventricular volumes, EF, tissue characterisation and perfusion.	Reduce acquisition time, enhance image quality and automate analysis.	DL techniques, under-sampling reconstruction, generative networks, CNN (Ruijsink et al [48]).	2-3x faster imaging, high-quality cine-MRI, automated structure-function quantification.
Cardiac CT	Assessment and characterisation of coronary arteries, estimation of lesion significance.	Segmentation, FFR estimation, calcium scorin.	DL pipeline (U-Net), multi-scale CNN (Zreik et al [49]), ML-based calcium scoring.	High agreement in FFR, rapid non-invasive assessment and accurate calcium scoring
Coronary artery interventions	First-line management of MI and ischaemic heart disease through PCI.	Pre-interventional imaging, risk prediction, AI-guided FFR.	CCTA with DL/ML, AI-derived FFR from CCTA.	High sensitivity for stenosis, improved diagnosis and PCI planning.

MRI: magnetic resonance imaging; CT: computed tomography; ECG: electrocardiogram; CNN: convolutional neural network; NLP: natural language processing; MI: myocardial infarction; DL: deep learning; ML: machine learning; FFR: fractional flow reserve; CCTA: coronary computed tomography angiography;

HF is a significant and complex health problem that affects millions of people globally. The current traditional medical methods are useful in most cases, however they are limited to detecting HF at an early stage, to assess each person’s risk level and to customise treatment options. More recently, AI, especially ML and DL have been transforming the way cardiovascular medicine is practiced. Specifically, AI technologies have provided practitioners tools to better diagnose HF, assist in making difficult clinical decisions and develop tailored interventions.

In this article we will outline how the delivery of HF care is transitioning from conventional practices to those supported through AI. With the use of advanced algorithms, AI now assists in the analysis of ECGs, echocardiography, cardiac MRI and CT scans allowing clinicians to recognise HF earlier and with greater accuracy.

AI can further help clinicians classify patients into their respective phenotypes of HF such as HFpEF, HFReEF, HFmrEF and HFimpEF. AI-assisted classification may facilitate more targeted treatments. Another area where AI is being utilised is the prediction of clinical outcomes in patients with HF; identification of candidates for device-based therapies; planning of coronary and structural interventions; and optimising the management of mechanical circulatory support. AI is able to generate rapid and actionable insights using large amounts of clinical data, multimodal imaging and biomarkers more so than traditional statistical methods. The AI-driven platforms utilising clinical data (electronic health records), imaging data and biological signatures also support the development of patient-specific care pathways in the management of HF. Patient-specific care has the

potential to lead to improvements in the quality of life, fewer hospitalisations due to HF and increased long term survival for individuals suffering from HF.

Conclusion

AI is now rapidly changing how HF is cared for through early detection and management at all levels of care. Advanced AI based ML models, will improve diagnostic accuracy, better define the phenotypes of different types of HF and provide clinicians with better ways to identify patients who can be grouped into clinically relevant risk groups. At the same time, predictive AI models will be increasingly used to predict an individual's response to drug or device therapy, optimise follow-up visits and streamline routine work within clinical workflow systems. The future development of AI in cardiology will continue to expand as both the number and detail of data sources grow and computational methods become more advanced. As such this trend is likely to lead to a model of care where timely decisions are made, patient treatment plans are developed on an individual basis and efficient care pathways are created and integrated into daily practice. However, it is no certainty that AI technology will be successfully translated into real world settings. The successful implementation of AI technologies within clinical settings will depend upon rigorous validation of the effectiveness of AI technologies, transparency of methodology in the development of AI technologies and strong governance surrounding the areas of data pri-

vacy and bias, as well as continued collaboration between clinicians, engineers/data scientists and regulatory agencies. As long as the above criteria are addressed, AI could provide an effective means of enhancing HF care which is both precise, equitable, trustworthy and patient-focused.

Ethics

This study was a secondary analysis based on currently existing data and did not directly involve with human participants or experimental animals. Therefore, the ethics approval was not required in this paper.

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Conflicts of interest

The authors declare that there is no conflict of interest.

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Data access

The data that support the findings of this study are available from the corresponding author upon reasonable individual request.

Author ORCID numbers

Sunil Junapudi (SJ):
0000-0002-9216-6096
Maseer Khan (MK):
0000-0002-0165-5872
Syam Sundar Junapudi (SSJ):
0000-0003-4355-5455
Malavika Maduri (MM):
0009-0009-6157-6816
Tapasya Pamu (TP):
0009-0000-8655-4677
Kondati Pranathi (KP):
0009-0008-3458-2922
Sonia Arora (SA):
0009-0005-6194-7550
Hitesh Chopra (HC):
0000-0001-8867-7603
Shivani Chopra (SC):
0000-0002-2871-086X

Author contributions

Conceptualisation: SJ, HC
Methodology: MK
Software: KP
Validation: MK, KP
Formal analysis: TP
Investigation: SSJ, SA
Resources: SSJ, SA
Data curation: MM
Writing - original draft: SJ, MM, HC
Writing - review and editing: MK, SSJ, TP, KP, SA, SC
Visualisation: LL, SC

References

1. Yasmin F, Shah SM, Naeem A, Shujaiddin SM, Jabeen A, Kazmi S, et al. Artificial intelligence in the diagnosis and detection of heart failure: the past, present, and future. *Rev Cardiovasc Med*. 2021;22(4):1095-113. doi: 10.31083/j.rcm2204121.
2. Boichenko V, Noakes VM, Reilly-O'Donnell B, Luciani GB, Emanuelli C, Martelli F, Gorelik J. Circulating non-coding RNAs as indicators of fibrosis and heart failure severity. *Cells*. 2025;14(7):553. doi: 10.3390/cells14070553.
3. Shams P, Malik A, Chhabra L. Heart Failure (Congestive Heart Failure). In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2025. PMID:28613623.

4. Inamdar AA, Inamdar AC. Heart failure: diagnosis, management, and utilization. *J Clin Med.* 2016;5(7):62. doi: 10.3390/jcm5070062.
5. Khan MS, Arshad MS, Greene SJ, Van Spall HGC, Pandey A, Vemulapalli S, et al. Artificial intelligence and heart failure: a state-of-the-art review. *Eur J Heart Fail.* 2023;25:1507-25. doi: 10.1002/ehf.2994.
6. Shah SJ, Kitzman DW, Borlaug BA, Van Heerebeek L, Zile MR, Kass DA, et al. Phenotype-specific treatment of heart failure with preserved ejection fraction: a multiorgan roadmap. *Circulation.* 2016;134(1):73-90. doi: 10.1161/CIRCULATIONAHA.116.021884.
7. Das BB. Novel therapies for right ventricular failure. *Curr Cardiol Rep.* 2025;27(1):26. doi: 10.1007/s11886-024-02157-9.
8. Yoon M, Park JJ, Hur T, Hua CH, Hussain M, Lee S, Choi DJ. Application and potential of artificial intelligence in heart failure: past, present, and future. *Int J Heart Fail.* 2023;6(1):11. doi: 10.36628/ijhf.2023.0050.
9. Kitzman DW, Brubaker P, Morgan T, Haykowsky M, Hundley G, Kraus WE, et al. Effect of caloric restriction or aerobic exercise training on peak oxygen consumption and quality of life in obese older patients with heart failure with preserved ejection fraction: a randomized clinical trial. *JAMA.* 2016;315(1):36-46. doi: 10.1001/jama.2015.17346.
10. Ovchinnikov A, Potekhina A, Arefieva T, Filatova A, Ageev F, Belyavskiy E. Use of statins in heart failure with preserved ejection fraction: current evidence and perspectives. *Int J Mol Sci.* 2024;25(9):4958. doi: 10.3390/ijms25094958.
11. Redfield MM, Anstrom KJ, Levine JA, Koepp GA, Borlaug BA, Chen HH, et al. Isosorbide mononitrate in heart failure with preserved ejection fraction. *N Engl J Med.* 2015;373(24):2314-24. doi: 10.1056/NEJMoa1510774.
12. Gevaert AB, Tibebu S, Mamas MA, Ravindra NG, Lee SF, Ahmad T, et al. Clinical phenogroups are more effective than left ventricular ejection fraction categories in stratifying heart failure outcomes. *ESC Heart Fail.* 2021;8(4):2741-54. doi: 10.1002/ehf2.13344.
13. Ahmad T, Lund LH, Rao P, Ghosh R, Warier P, Vaccaro B, et al. Machine learning methods improve prognostication, identify clinically distinct phenotypes, and detect heterogeneity in response to therapy in a large cohort of heart failure patients. *J Am Heart Assoc.* 2018;7(8):e008081. doi: 10.1161/JAHA.117.008081.
14. Shakibfar S, Krause O, Lund-Andersen C, Aranda A, Moll J, Andersen TO, et al. Predicting electrical storms by remote monitoring of implantable cardioverter-defibrillator patients using machine learning. *EP Europace.* 2019;21(2):268-74. doi: 10.1093/europace/euy257.
15. Goretti F, Oronti B, Milli M, Iadanza E. Deep learning for predicting congestive heart failure. *Electronics.* 2022;11(23):3996. doi: 10.3390/electronics11233996.
16. Zhao J, Feng Q, Wu P, Lupu RA, Wilke RA, Wells QS, et al. Learning from longitudinal data in electronic health records and genetic data to improve cardiovascular event prediction. *Sci Rep.* 2019;9(1):717. doi: 10.1038/s41598-018-36745-x.
17. Adler ED, Voors AA, Klein L, Macheret F, Braun OO, Urey MA, et al. Improving risk prediction in heart failure using machine learning. *Eur J Heart Fail.* 2020;22(1):139-47. doi: 10.1002/ehf.1628.
18. Golas SB, Shibahara T, Agboola S, Otaki H, Sato J, Nakae T, et al. A machine learning model to predict the risk of 30-day readmissions in patients with heart failure: a retrospective analysis of electronic medical records data. *BMC Med Inform Decis Mak.* 2018;18(1):44. doi: 10.1186/s12911-018-0620-z.
19. Nabrdalik K, Kwiendacz H, Irlík K, Hendel M, Drożdż K, Wijata AM, et al. Machine learning identification of risk factors for heart failure in patients with diabetes mellitus with metabolic dysfunction-associated steatotic liver disease (MASLD): the Silesia Diabetes-Heart Project. *Cardiovasc Diabetol.* 2023;22(1):318. doi: 10.1186/s12933-023-02014-z.
20. Ahn I, Gwon H, Kang H, Kim Y, Seo H, Choi H, et al. Machine learning-based hospital discharge prediction for patients with cardiovascular diseases: development and usability study. *JMIR Med Inform.* 2021;9(11):e32662. doi: 10.2196/32662.
21. Bhatt CM, Patel P, Ghetia T, Mazzeo PL. Effective heart disease prediction using machine learning techniques. *Algorithms.* 2023;16(2):88. doi: 10.3390/a16020088.
22. Hasan N, Bao Y. Comparing different feature selection algorithms for cardiovascular disease prediction. *Health Technol.* 2021;11(1):49-62. doi: 10.1007/s12553-020-00499-2.
23. Chowdhury MA, Rizk R, Chiu C, Zhang JJ, Scholl JL, Bosch TJ, et al. The heart of transformation: exploring artificial intelligence in cardiovascular disease. *Biomedicines.* 2025;13(2):427. doi: 10.3390/biomedicines13020427.
24. Hannun AY, Rajpurkar P, Haghpanahi M, Tison GH, Bourn C, Turakhia MP, Ng AY. Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. *Nat Med.* 2019;25(1):65-9. doi: 10.1038/s41591-018-0268-3.
25. Karatzia L, Aung N, Aksentijevic D. Artificial intelligence in cardiology: Hope for the future and power for the present. *Front Cardiovasc Med.* 2022;9:945726. doi: 10.3389/fcvm.2022.945726.
26. Zhang J, Gajjala S, Agrawal P, Tison GH, Hallock LA, Beussink-Nelson L, et al. Fully automated echocardiogram interpretation in clinical practice: feasibility and diagnostic accuracy. *Circulation.* 2018;138(16):1623-35. doi: 10.1161/CIRCULATIONAHA.118.034338.
27. Miller JG, Li M, Mazilu D, Hunt T, Horvath KA. Robot-assisted real-time magnetic resonance image-guided transcatheter aortic valve replacement. *J Thorac Cardiovasc Surg.* 2016;151(5):1407-12. doi: 10.1016/j.jtcvs.2015.11.047.
28. Alsharqi M, Edelman ER. Artificial intelligence in cardiovascular imaging and interventional cardiology: emerging trends and clinical implications. *J Soc Cardiovasc Angiogr Interv.* 2025;4(3):102558. doi: 10.1016/j.jscai.2024.102558.
29. Bavo AM, Wilkins BT, Garot P, De Bock S, Saw J, Søndergaard L, et al. Validation of a computational model aiming to optimize preprocedural planning in percutaneous left atrial appendage closure. *J Cardiovasc Comput Tomogr.* 2020;14(2):149-54. doi: 10.1016/j.jcct.2019.08.01.
30. Fahmy AS, Rausch J, Neisius U, Chan RH, Maron MS, Appelbaum E, et al. Automated cardiac MR scar quantification in hypertrophic cardiomyopathy using deep convolutional neural networks. *JACC Cardiovasc Imaging.* 2018;11(12):1917-8. doi: 10.1016/j.jcmg.2018.04.030.
31. Shade JK, Ali RL, Basile D, Popescu D, Akhtar T, Marine JE, et al. Preprocedure application of machine learning and mechanistic simulations predicts the

- likelihood of paroxysmal atrial fibrillation recurrence following pulmonary vein isolation. *Circ Arrhythm Electrophysiol.* 2020;13(7):e008213. doi: 10.1161/CIRCEP.119.008213.
32. Srinivasan SM, Sharma V. Applications of AI in cardiovascular disease detection: A review of the specific ways in which AI is being used to detect and diagnose cardiovascular diseases. In: *AI in Disease Detection: Advancements and Applications.* 2025:123-46. doi: 10.1002/9781394278695.ch6.
 33. Yang G, Ren Y, Pan Q, Ning G, Gong S, Cai G, et al. A heart failure diagnosis model based on a support vector machine. In: *2010 3rd International Conference on Biomedical Engineering and Informatics.* Vol 3. IEEE; 2010. p.1105-1108. doi: 10.1109/BMEI.2010.5639619.
 34. Gharehchopogh FS, Khalifelu ZA. Neural network application in the diagnosis of patients: a case study. In: *International Conference on Computer Networks and Information Technology.* IEEE; 2011. p.245-249. doi: 10.1109/ICCINIT.2011.6020937.
 35. Son CS, Kim YN, Kim HS, Park HS, Kim MS. Decision-making model for early diagnosis of congestive heart failure using rough set and decision tree approaches. *J Biomed Inform.* 2012;45(5):999-1008. doi: 10.1016/j.jbi.2012.04.013.
 36. Wu J, Roy J, Stewart WF. Prediction modeling using EHR data: challenges, strategies, and a comparison of machine learning approaches. *Med Care.* 2010;48(6 Suppl):S106-13. doi: 10.1097/MLR.0b013e3181de9e17.
 37. Aljaaf AJ, Al-Jumeily D, Hussain AJ, Dawson T, Fergus P, Al-Jumaily M. Predicting the likelihood of heart failure with a multi-level risk assessment using decision tree. In: *2015 Third International Conference on Technological Advances in Electrical, Electronics and Computer Engineering (TAECE).* IEEE; 2015. p.101-106. doi: 10.1109/TAECE.2015.7113608.
 38. Masetic Z, Subasi A. Congestive heart failure detection using random forest classifier. *Comput Methods Programs Biomed.* 2016;130:54-64. doi: 10.1016/j.cmpb.2016.03.020.
 39. Zheng Y, Guo X, Qin J, Xiao S. Computer-assisted diagnosis for chronic heart failure by the analysis of their cardiac reserve and heart sound characteristics. *Comput Methods Programs Biomed.* 2015;122(3):372-83. doi: 10.1016/j.cmpb.2015.09.001.
 40. Akinyokun CO, Obot OU, Uzoka FM. Application of neuro-fuzzy technology in medical diagnosis: case study of heart failure. In: *World Congress on Medical Physics and Biomedical Engineering.* Springer; 2009. p.301-304. doi: 10.1007/978-3-642-03893-8_86.
 41. Pecchia L, Melillo P, Bracale M. Remote health monitoring of heart failure with data mining via CART method on HRV features. *IEEE Trans Biomed Eng.* 2010;58(3):800-4. doi: 10.1109/TBME.2010.2092776.
 42. Melillo P, De Luca N, Bracale M, Pecchia L. Classification tree for risk assessment in patients suffering from congestive heart failure via long-term heart rate variability. *IEEE J Biomed Health Inform.* 2013;17(3):727-33. doi: 10.1109/JBHI.2013.2244902.
 43. Sideris C, Alshurafa N, Pourhomayoun M, Shahmohammadi F, Samy L, Sarrafzadeh M. A data-driven feature extraction framework for predicting the severity of the condition of congestive heart failure patients. In: *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).* IEEE; 2015. p.2534-2537. doi: 10.1109/EMBC.2015.7318908.
 44. Katz DH, Deo RC, Aguilar FG, Selvaraj S, Martinez EE, Beussink-Nelson L, Kim KY, Peng J, Irvin MR, Tiwari H, Rao DC. Phenomapping for the identification of hypertensive patients with the myocardial substrate for heart failure with preserved ejection fraction. *J Cardiovasc Transl Res.* 2017;10(3):275-84. doi: 10.1007/s12265-017-9739-z.
 45. Przewlocka-Kosmala M, Marwick TH, Dabrowski A, Kosmala W. Contribution of cardiovascular reserve to prognostic categories of heart failure with preserved ejection fraction: a classification based on machine learning. *J Am Soc Echocardiogr.* 2019;32(5):604-15. doi: 10.1016/j.echo.2018.12.002.
 46. Shah SJ, Katz DH, Selvaraj S, Burke MA, Yancy CW, Gheorghide M, et al. Phenomapping for novel classification of heart failure with preserved ejection fraction. *Circulation.* 2015;131(3):269-79. doi: 10.1161/CIRCULATIONAHA.114.01063.
 47. Tripoliti EE, Papadopoulos TG, Karanasiou GS, Naka KK, Fotiadis DI. Heart failure: diagnosis, severity estimation, and prediction of adverse events through machine learning techniques. *Comput Struct Biotechnol J.* 2017;15:26-47. doi: 10.1016/j.csbj.2016.11.001.
 48. Ruijsink B, Puyol-Antón E, Oksuz I, Sinclair M, Bai W, Schnabel JA, et al. Fully automated, quality-controlled cardiac analysis from CMR: validation and large-scale application to characterize cardiac function. *Cardiovasc Imaging.* 2020;13(3):684-95. doi: 10.1016/j.jcmg.2019.05.030.
 49. Zreik M, Lessmann N, van Hamersvelt RW, Wolterink JM, Voskuil M, Viergever MA, et al. Deep learning analysis of the myocardium in coronary CT angiography for identification of patients with functionally significant coronary artery stenosis. *Med Image Anal.* 2018;44:72-85. doi: 10.1016/j.media.2017.11.008.