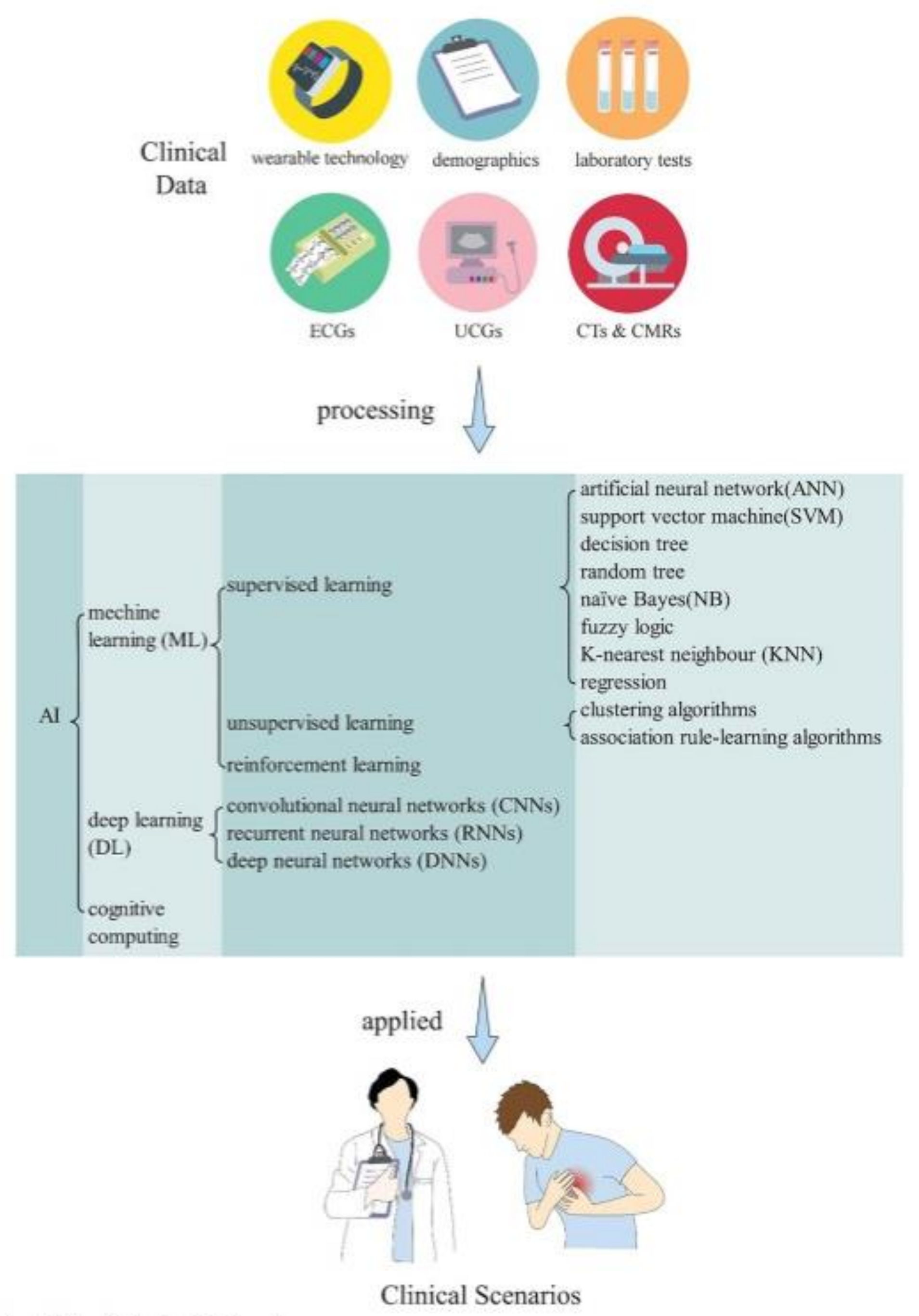
Artificial intelligence in cardiovascular diseases: diagnostic and therapeutic perspectives

Introduction

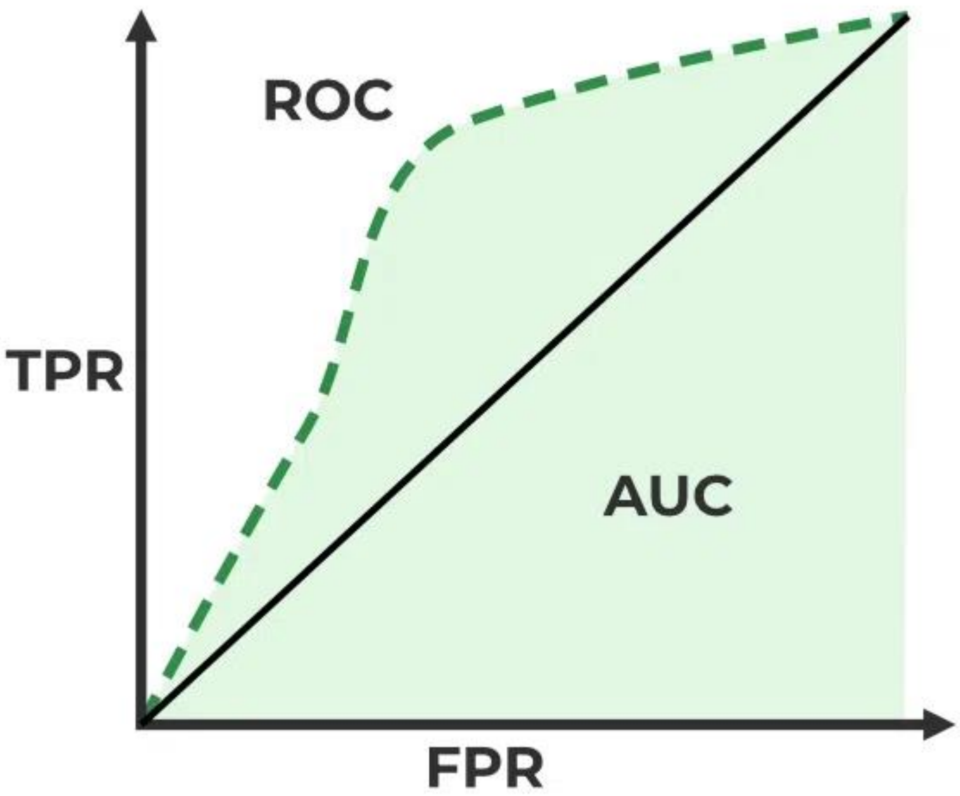
- What is Artificial Intelligence (AI)?
- What can AI offer in clinical settings?
- Different types of Machine Learning
- Most common types of Machine learning algorithms for medical purposes

Flowchart of AI in clinical settings



Receiver Operating Characteristic (ROC) curve and area under the curve (AUC)

		Actual	
		Positive	Negative
Predicted	Positive	True Positive	False Positive
	Negative	False Negative	True Negative



Types and situations of using AI in cardiovascular medicine

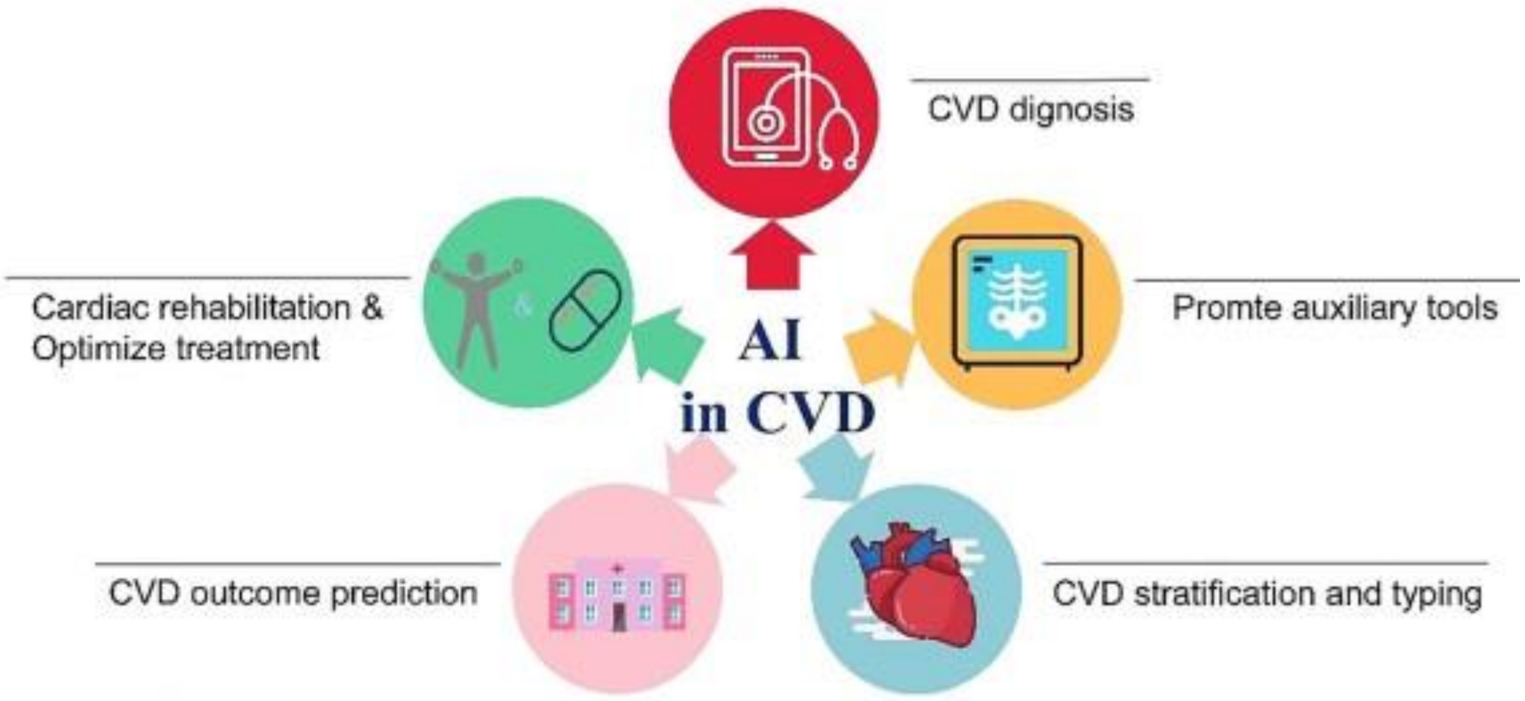


Fig. 2 Situation of AI application in CVD

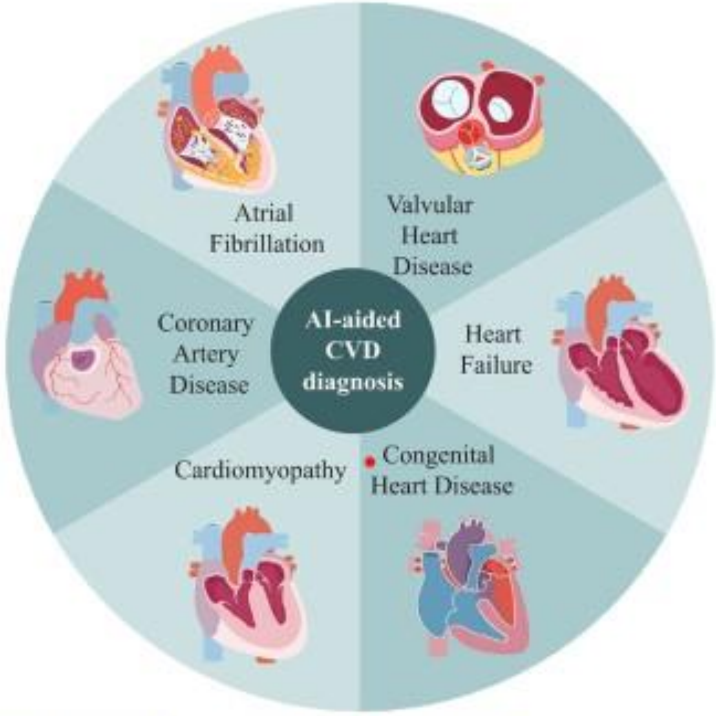


Fig. 3 Types of diseases of AI application in CVD

AI-aided CVD diagnosis

- difficulties in screening and early diagnosis of CVDs
- unlocking ECG's potential with AI !

Diagnosis of Valvular heart diseases

- long asymptomatic periods
- Increased mortality as symptoms appear
- Good outcomes with intervention started before symptom presentation
- AI-ECG
- DL-based algorithm to detect moderate or severe aortic stenosis (AS) using ECGs → AUC= 0.86 - 0.90 using sex and age
- focused on the T wave of the precordial lead
- ***negative predictive value was > 99%***
- **Valve Net** DL model for moderate or severe AS, aortic regurgitation (AR), and mitral regurgitation (MR)

Diagnosis of Atrial fibrillation

- asymptomatic and elusive; especially paroxysmal AF
- underdiagnosis
- subtle structural changes
- A CNN to identify patients with AF during normal sinus rhythm using 500,000 ECGs →AUC = 0.87; accuracy =79%

When using all ECGs from 31 days before AF rhythm → AUC = 0.90; accuracy =88 %

- Improving the performance of CHARGE-AF (Cohorts for Heart and Aging Research in Genomic Epidemiology-Atrial Fibrillation)
- Higher stroke risk calculated with AI-ECG of NSR corresponded to a significantly higher rate of AF diagnosis

Diagnosis of Coronary artery disease

- AUC of 0.80 per patient and 0.76 per vessel for detecting CAD on angiography using SPECT MPI taken within 6 months
- AUC of 0.73 and the accuracy of 68% for detecting CAD from facial features

Diagnosis of Heart failure

- Echocardiogram is costly and unavailable for screening
- LVHF can be asymptomatic
- Early diagnose of LVHF can lead to better outcomes
- Large neural networks using ECG for HF screening → AUC =0.93, with an accuracy of 86 %

positive AI-ECG but negative echocardiography → HR = 4

- Giving primary teams access to AI-ECG increases HF diagnosis by 32 %
- Right ventricular dysfunction is closely related to the left and total heart failure
- A DL model with an AUC of 0.84 for RV HF detection and AUC of 0.94 for LV HF detection

Diagnosing Cardiomyopathy

- Familial risk of DCM and sudden death
- Routine echocardiographic screening is impractical
- a CNN model to achieve the early diagnosis of DCM using ECG → AUC to detect LVEF≤45% = 0.955, ***with a negative predictive value of more than 99%***
- CMR: the gold standard for LVH diagnosis but impractical for screening
- A CNN model using 32,239 ECGs → AUC of 0.653 and 0.621 in 2 independent tests
- Sudden cardiac death of HCM is *preventable*!
- Diagnosis of HCM : echocardiography; mostly indistinguishable abnormalities
- Using AI-ECG for HCM screening :AUC =0.96 with the sensitivity = 87% and specificity o=90%. Surprisingly, ***this model performed particularly well in young individuals*** → ***high potential for screening***
- DL models for SPECT, CTS, Ultrasound,even facial features!

Diagnosing Congenital heart disease

- most common congenital disability; significant mortality
- Lack of specialized sonographers or missing critical image frames
- A CNN using nearly 100,000 images from echocardiographic and screening ultrasound from 18 to 24 weeks ***AUC of 0.99 , a negative predictive value of 100% !***

Robust performance on outside-hospital and lower-quality images

AI enhancing the effectiveness of auxiliary tools

- LVEF detection using AI from echocardiograms; similar accuracy as clinicians; point of care monitoring
- CNN for detecting abnormal wall motion in patients with MI

AI: AUC=0.99

Cardiologists and Sonographers: AUC=0.98

Residents :AUC =0.90

AI enhancing the effectiveness of auxiliary tools

- CCTA: effective and non-invasive; but costly and time-consuming; requires semi-automated manual evaluation
- DL models with accuracies similar to expert consensus
- Myocardial blood flow (MBF) and myocardial perfusion reserve (MPR) assessed with a DL model : independent predictor of cardiac prognosis
- invasive fractional flow reserve (FFR) $< 0.80 \rightarrow$ lower accuracy of angiography for CAD diagnosis
- ML models using angiography images $\rightarrow$ AUC = 0.84

AI-aided CVD stratification and typing

- cardiac resynchronization therapy (CRT) patient selection
- Unsupervised ML model: 4 patient categories; two of which responded substantially better to ICD
- Clustering algorithm able to detect positive beta blocker response both in AF and sinus rhythm
- AF clinical data clustering for SCD risk stratification and prognosis
- Aortic pressure damping during angiography classification with an accuracy of 99.4%

AI-aided CVD stratification and typing

- Phonotypical and prognostic heterogeneity of HTN
- *Clustering of hypertensive patients of SPRINT trial and intensive BP control*
- *Distinguishing PHT from EHT using Momics and ML*
- *Predicting HCM genotype using CMR*

AI-aided CVD outcome prediction

- All-cause mortality calculation using large ECG datasets
- ECG-derived age and chronological age mismatch
- Automatic retinal vessel caliber calculation
- Detecting most important prognostic features
- Predicting stent underexpansion using IVUS
- Predicting clinical outcomes using PT-INR time series
- Predicting hospital re-admission after surgical aortic valve replacement

Limitations

- Black box feature selection
- Concentrated and scarce research centers and datasets
- cost-effectiveness and impact on clinical practice