Machine learning in sudden cardiac death risk prediction: a systematic review

Joseph Barker[1,2], Xin Li[1,3], Sarah Khavandi[4], David Koeckerling[5], Akash Mavilakandy[1], Coral Pepper[6], Vasiliki Bountziouka[1], Long Chen[7], Ahmed Kotb[1,2], Ibrahim Antoun[1], John Mansir[8], Karl Smith-Byrne[9], Fernando S Schlindwein[1,3], Harshil Dhutia[1,2], Ivan Tyukin[10], William B Nicolson[1,2], G Andre Ng*[1,2,11]

Affiliations:

1. Department of Cardiovascular Sciences, University of Leicester, Leicester, UK

2. Cardiology Department, Glenfield Hospital, University Hospitals Leicester, Leicester, UK

3. School of Engineering, University of Leicester, Leicester, UK

4. Imperial College School of Medicine, Imperial College London, London, UK

5. Div. of Angiology, Swiss Cardiovascular Center, Inselspital, Bern Uni. Hosp., University of Bern, Bern, Switzerland

6. Library and Information Service, University Hospitals of Leicester NHS Trust, Leicester, UK

7. School of Computing and Mathematical Sciences, University of Leicester, Leicester, UK

8. Independent Scholar, London, UK.

9. Cancer Epidemiology Unit, Nuffield Dept. of Population Health, University of Oxford, Oxford, UK

10. Department of Mathematics, University of Leicester, Leicester, UK

11. National Institute for Health Research, Leicester Biomedical Research Centre, Leicester, UK

Main text word count: 3621

Abstract word count: 250

*Corresponding author:

Professor G André Ng

Head of Department

Professor of Cardiac Electrophysiology

Consultant Cardiologist & Electrophysiologist

Email: andre.ng@leicester.ac.uk

Telephone: +44(0)1162044752

Abstract

Background: Most patients that receive implantable cardioverter defibrillators (ICDs) for primary prevention do not receive therapy during the lifespan of the ICD, whilst up to 50% of sudden cardiac death (SCD) occur in individuals that are considered low risk by conventional criteria. Machine learning offers a novel approach to risk stratification for ICD assignment.

Methods: Systematic search was performed in MEDLINE, Embase, Emcare, CINAHL, Cochrane Library, OpenGrey, MedrXiv, arXiv, Scopus & Web of Science. Studies modelling SCD risk prediction within days to years using machine learning were eligible for inclusion. Transparency & quality of reporting (TRIPOD) and risk of bias (PROBAST) were assessed.

Results: 4,356 studies were screened with 11 meeting the inclusion criteria with heterogeneous populations, methods and outcome measures preventing meta-analysis. Study size ranged from 122 to 124,097 participants. Input data sources included demographic, clinical, electrocardiogram, electrophysiological, imaging and genetic data ranging from 4 to 72 variables per model. The most common outcome metric reported was area under the receiver operator characteristic (n=7) ranging between 0.71-0.96. In six studies comparing machine learning models and regression, machine learning improved performance in five. No studies adhered to a reporting standard. Five of the papers were high risk of bias.

Conclusion: Machine learning for SCD prediction has been under-applied and incorrectly implemented but is ripe for future investigation. It may have some incremental utility in predicting SCD over traditional models. The development of reporting standards for machine learning are required to improve the quality of evidence reporting in the field.

What's new?

- Machine learning may have some incremental utility in predicting sudden cardiac death over traditional techniques
- The complexity of data that might be used to inform ICD assignment lends itself to deep learning methods
- Reporting guidelines for machine learning studies are required to improve the transparency and reproducibility of studies.

Background:

Sudden cardiac death (SCD) is a major global public health issue attributable to over 4 million deaths a year (1). It represents a terminal event of a heterogenous group of cardiac diseases that require a combination of arrhythmogenic substrate (diseased myocardium) and precipitating event to cause cardiac arrest (2). Implantable cardioverter defibrillators (ICDs) can abort SCD caused by malignant ventricular arrhythmias by defibrillation or anti-tachycardia pacing. However, current primary prevention strategies are inadequate. Evidence from the landmark MADIT II and SCD-HeFT trials suggest 60% of patients receiving ICDs do not require ICD therapy during the majority of its battery lifespan, whilst exposing patients to procedural complications and burdening health systems (3-6). Koller et al. goes further to describe as much as 11% of patients dying without ever requiring any ICD therapy after implantation (7). Meanwhile patients continue to die from SCD who are conventionally estimated to be low to intermediate risk, historically with up to 50% of SCD occurring in individuals without known heart disease (8).

The challenge of SCD prediction, described by the European Society of Cardiology (ESC) as the philosopher's stone of arrhythmology, is to predict in which patients malignant ventricular arrythmia will take place, and to do so within the battery life of an ICD (10-13 years) such that an ICD can be implanted effectively (1). To date many novel risk stratification tools have been proposed, but none performed sufficiently in external validation to be implemented in clinical practice (9). An alternative to traditional methods is machine learning - a subfield of artificial intelligence that uses data-driven computational modelling to identify complex patterns in data. Recent advances in machine learning algorithms, scalable cloud computing power and the availability of wide (large cohorts) and long (detailed and highly varied) data have allowed computers to learn relationships contained in data without being given specific instructions by a

human on what those relationships are, and therefore make accurate predictions on unseen data (10). Indeed, there is growing evidence that machine learning models may classify patients with similar or greater accuracy than clinicians outside of SCD (11,12), and are able to derive patterns in the electrocardiogram (ECG) that are otherwise not apparent to the human eye (13). Thus, we sought to perform a systematic review of published machine learning models used to predict SCD that might improve assignment of ICDs.

Methods:

This systematic review was conducted in accordance with the Preferred Reporting Items for a Systematic Review and Meta-analysis of Diagnostic Test Accuracy Studies (PRISMA-DTA) statement (14). PRISMA-DTA checklist available in supplement. The study protocol was registered on the international prospective register of systematic reviews PROSPERO (ID number CRD42021248582).

Search Strategy & Study Selection

A search strategy was performed with a variety of keywords and thesaurus terms in the structure: 'sudden cardiac death' AND 'risk prediction' AND 'machine learning'. Papers on both primary and secondary sudden cardiac death risk prediction were included. Databases used in the search included MEDLINE, Embase, Emcare, CINAHL, Cochrane Library (including CENTRAL, NIH registry & CTRI), OpenGrey, MedrXiv, arXiv, Scopus (including Compendex) & Web of Science without any restriction. No date or language limits were applied to the search strategy, but a human-only filter was used. Conference abstracts were included to identify models that were published in full text elsewhere, but were excluded from the review. A full strategy can be found in the data supplement.

Data extraction

Duplicate records were identified using RefWorks and deleted before screening. Data extraction was completed using Google Sheets. Two reviewers (JB & DK) independently performed the title and abstract screening. Full text review was undertaken by JB and AM. Disagreement was adjudicated by postdoctoral biomedical engineer (XL). For full text article screening the reason for exclusion was recorded. Data was extracted by JB and SK. All key articles had references reviewed to identify further studies.

Eligibility criteria and study selection

Studies were eligible if they aimed to predict a SCD event in an adult population using machine learning methods sufficiently in advance (1 day) as to allow for ICD implantation. Hence studies predicting the onset of SCD within minutes to hours were excluded as well as studies that used machine learning for feature extraction without SCD status being a key target variable in the model or outcome. Studies were required to have six months follow up from initial assessment, either prospectively or retrospectively, so as to also allow sufficient time for a significant SCD event to occur within the population. A sudden cardiac death event was defined as a death classified as SCD, aborted cardiac arrest, sustained VT, VF, implantable cardioverter defibrillation or anti-tachycardia pacing. The studies were required to be in English, have a total number of patients of N>50 and provide a description of the machine learning models and predictor variables used in risk prediction. Data collected from the studies included author information, year of publication, variables used in the model, population studied, machine learning prediction model type and model performance metrics including area under the receiver operating characteristic (AUC), sensitivity and specificity, positive predictive values, negative predictive values, area under the precision-recall curve, model accuracy, precision and recall, F1 score and odds/hazard

ratios/relative risk (OR/HR/RR). Other variables collected were number of patients in the study, database information, SCD definition and length of follow up.

Quality of evidence and risk of bias

There are no consensus methods of assessing the quality of machine learning prognostic prediction model studies, though this need has been recognised and these methods are under development (15). The Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) statement was used to assess paper transparency and quality, whilst the Prediction model study Risk Of Bias Assessment Tool (PROBAST) was used to assess bias (16,17). Two review authors (JB and XL) independently scored the key studies and with discrepancies settled by (AN).

Results:

Study selection

A total of 4,356 studies were screened. From these, 434 full texts were reviewed resulting in 11 studies that met the inclusion criteria for the systematic review, table 1. Reasons for the exclusion at full text review were recorded and can be found in figure 1.

Study characteristics

Substantial heterogeneity in populations, methods and outcome measures were identified in papers dating back to 2001. Populations spanned Europe (n=3)(18-20), North America (n=3)(21-23) and Asia (n=2)(24,25) with three cohort studies being multinational (26-28). Disease cohorts under investigation included ischaemic cardiomyopathy (n=2)(18,22) Brugada syndrome (n=2)(25,26), unselected heart failure with reduced ejection fraction (n=1)(24), non-ischaemic cardiomyopathy (n=1)(19), hypertrophic cardiomyopathy (HCM) (n=1)(20), end stage renal

failure on dialysis (n=1)(21), unselected disease cohorts undergoing ventricular tachycardia (VT) ablation or ICD implants (n=2)(23,27) and tetralogy of Fallot (28).

Seven studies were retrospective cohorts (21,23-28) and the majority employed supervised machine learning techniques (n=9) to identify correlates with outcomes (18,19,21-24,27-28). Three studies employed unsupervised methods (20,25,26), with Lee *et al.* (25) employing both. The most popular machine learning techniques were random forests (n=6)(21,23-25,27,28) followed by support vector machines (n=3)(19,22,24) and non-negative matrix factorisation (n=2)(25,26). Input data for the machine learning models included demographic, clinical, electrocardiogram, imaging, electrophysiological and genetic data ranging from 4 to 72 data sources per model, median 10 (IQR 8-21). Studies had a median number of patients of 376 but ranged from as low as 122 to 124,097 participants. Median follow up was 33 months (IQR 26-45). SCD outcomes included sustained VT or ventricular fibrillation (VF), cardiac arrest, electrical storm, appropriate ICD fire, SCD coded in an electronic health record and deaths adjudicated by clinicians as SCD. Only Lyon et al. (20) employed a surrogate outcome measure by correlating the outputs of an unsupervised algorithm to the HCM Risk-SCD score in order to phenotype HCM patients (29). Most models employed hold-out validation strategies whereby data is segregated prior to training to keep a validation cohort unseen to then test the accuracy of risk models (n=6)(18,21,23,24,26,27). Four of the six papers were cross-validated(21,24-26). Only one, Tse et al.(26), externally validated their model in an international Brugada cohort. The median number of SCD events per paper was 53 (IQR 28-268). The most common outcome measure reported was AUC (n=7)(19,21-23,24,26,27), ranging from 0.71(22) to 0.96(19), and OR/HR/RR (n=4)(18,22,25,27), maximally HR=24.0 (95% CI, 1.21 to 479, p=0.037)(25), figure 2. Sensitivity or specificity were reported in five studies (18,19,22,23,28), whilst precision, recall and F1 scores

in two studies(25,26). Two studies volunteered the capacity to share data (25,26) and no studies shared access to code used in their machine learning analysis and no studies reported adhering to a reporting standard.

Given the low number of studies that met the inclusion criteria coupled with the substantial heterogeneity in populations, methods and performance metrics, it was inappropriate to estimate overall model performance by meta-analysis. However, in six studies that compared logistic or cox regression to machine learning methods (21,23,24-27), five out six machine learning models outperformed regressions modestly within their analyses (21,23,25,26,27), figure 2. The greatest improvement was seen with Lee et al. (25) with F1 scores incrementing from 0.74 to 0.88 within a Brugada cohort predicting VT and VF from multimodal data streams using 4-fold cross validation, figure 2.

Quality of evidence and risk of bias

The completeness of study reporting as measured by TRIPOD scoring was 78% (IQR 71-86%), figure 3. No studies were completely reported. Just two studies incorporated the use of blinding during analysis(20,22), whereby outcomes are hidden to researchers to reduce bias. No studies explained how the study size was arrived at. Just four studies explained how missing data was handled (20-22,28) and only one of the six hold-out training and validation studies described any comparison of important variables between the sub-cohorts (27). Just six models presented the full prediction model to allow predictions for individuals (18,22,25-28) and only three explaining how to use the prediction model (20,27,28).

In assessing the overall bias and applicability of using PROBAST, five studies were scored high risk of bias (18,19,23,24,27), four as unknown risk (21,25,26,28) and two as low risk (20,22), table 2, figure 4. The high risk of bias was due to model overfitting not being accounted for during

analysis (18,19,27), data imbalance (23), and treating continuous variables categorically (24). Unknown risk of bias arose from unspecified blinding (18,19,21,23-27), unclear handling of missing data (24,25) and a lack of detail of the validation datasets (18,21,23,24,26,27). No studies were scored as high risk for applicability, whilst all six hold-out training and validation studies scored as unclear risk due to underreporting validation and test cohorts (18,21,23,24,26,27), inconsistent reporting of results (19) and the age of the paper as with Zoni-Berriso et al. (18) who reported on myocardial infarction without revascularisation, a cohort that is exceedingly small today. Funding organisations and disclosures are summarised in table 3.

Discussion:

This is the first study to systematically review the use of machine learning to predict SCD showing it is in its infancy. Eleven studies reported a variety of machine learning models reporting overall good performance in predominantly retrospective data. Compared to regression, machine learning appears to show a modest incremental improvement in predictive ability, figure 2 & table 1, though applicability of the studies were limited due to a number of reasons explored below.

Under-reporting **-** Disappointingly for the majority of the studies there is insufficient detail of the machine learning models to replicate methods, and most do not provide sufficient description of both training and test cohorts. Tse et al.(26), a study investigating SCD in Brugada, is the only externally validated study, however without information regarding variable and outcome distributions of the validation cohort the applicability of the results become uncertain. No papers referenced a reporting standard and future studies should do so to limit the influence of underreporting on their work.

Overfitting **-** Overfitting refers to the scenario where a machine learning model performs well against its training data but fails to perform well on unseen data, largely when a model has a greater

capacity than the relevant information contained within the dataset. In effect the model spends this excess capacity learning the specifics of the noise in the training data, rather than discriminative features, which is not then the same in the validation data. Therefore, performance metrics on the validation cohort best represent model performance, rather than the training cohort. Studies should avoid representing training cohort performance as the model performance where validation has been undertaken, as with Vegara et al. (22), which is in keeping with Good Machine Learning Practice consensus guidance (30). There are techniques to overcome overfitting such as regularisation, dimensionality reduction and synthetic data creation (31), though were not employed regularly here, and in some cases overfitting can be benign(32). Simpler models find it harder to overfit and the role of the clinician in machine learning is to carefully select only relevant data that confer risk or protective signals as model inputs.

Data imbalance - Data imbalance, or class imbalance, is common challenge in machine learning and an inherent problem to the study of rare outcomes such as SCD. It refers to when the number of observations per class (SCD vs no SCD) is not equally distributed. The only paper that adequately dealt with the imbalance issue was Goldstein et al. where their sample was so large, capturing 1,697 SCD events, they were able to sample 1:1 SCD vs no SCD and retain a large sample (21). Data scientist can deal with class imbalance though data augmentation strategies though there is no substitution for starting with an accurately labelled, balanced dataset (33). Furthermore, standard classification metrics such as AUC, as was the convention in this body of literature, do not adequately represent model performance when datasets are imbalanced. For example, an imbalanced database with 99% no SCD and 1% SCD, the model can produce an "all-negative" prediction with an accuracy of 99%. Alternate performance metrics, such as F1 score, as used by Tse et al. (26) and Lee et al. (25) in their Brugada cohorts, are required for model

performance to be properly understood in the case of imbalanced datasets, as well as tools such as confusion matrices and precision recall curves.

Machine learning

Supervised vs Unsupervised

Supervised learning predominates the literature. It refers to when a machine learning algorithm has access to labels, categorical or continuous, alongside input variables. The algorithm learns the complex relationships between the input variables and the labels. Unsupervised learning refers to machine learning algorithms which aim to discover some hidden substructure in data without access to labels - examples are clustering or dimensionality reduction. The two best studies ranked as both low risk of bias and low concern for applicability are discussed below as exemplars of supervised and unsupervised learning studies.

Okada et al., developed and validated a supervised machine learning prediction model for ventricular arrhythmia from CMR late gadolinium myocardial scar enhancement in ischaemic cardiomyopathy. With participants labelled as having SCD and no SCD they demonstrated myocardial substrate spatial complexity can be quantified meaningfully with an AUC of 0.72, and a negative predictive value of 0.91 for the risk of ventricular arrhythmia at 5 years, with an OR 1.93 per quartile of complexity scoring(22).

Conversely, Lyon et al. deployed two sequential unsupervised algorithms to extract features from ECGs of participants with HCM and identified four distinct phenotypes of HCM that have different HCM Risk-SCD profiles and hypertrophy distributions. Specifically, they showed primary T wave inversion and normal QRS ECG phenotype are at greater risk of SCD than patients with normal T wave morphology (4% vs 1.8% predicted SCD events by HCM Risk SCD score over 5 years) (20).

Types of model

Random Forests - Random forests are a form of supervised learning model that construct multiple decision trees according to splits in features (e.g. "age <50") in a process known as *recursive partitioning*. During training each tree is provided a random subset of the data by *bagging* or *bootstrapping*, in doing so minimising surprises in the data (*data entropy)*. To make a prediction each tree looks at unseen data to make a prediction, where in the case of classification, the final decision is arrived at by seeing which class got the most votes by tallying up the entire ensemble of trees, known as ensemble learning (34). Random forests are the most common machine learning technique within the literature (21,23,24,25,27,28), likely because they require little configuration and are less prone to overfitting.

Support vector machines - Support vector machines are a supervised learning algorithm used for classification and regression, used in two papers identified by the review (19,22). They work by transforming input data into a higher dimensional space which may then allow for neat delineation between data of two classes with a single flat hyperplane which would not be possible in the original data space (35).

Non-negative matrix factorisation - Non-negative matrix factorisation is an unsupervised algorithm that extracts hidden features from datasets that amalgamate signals, such as an ECG, used in two Brugada papers (25,26). They work by splitting the signals with no negative elements up into the component parts and weights to apply to them, then be reconstructed into an alternative arrangement that may confer different meaning (36).

Future Direction - *Deep Learning*

Conventional models for SCD risk are largely based on tabular data with one or few designed inputs. Complex multi-dimensional data, such as systolic function or myocardial

depolarisation are usually reduced to summarised features such as ejection fraction and QRS duration, leaving behind complex hidden signals that otherwise might confer risk. The models themselves are relatively simple and may not have sufficient "depth" to capture the relationship between input and output variables (underfitting). More advanced machine learning models such as deep learning are able to preserve the complexity in multidimensional data, handle large number of variables and tackle more complex problems, which can therefore look beyond what tabular data analysis offers. More specifically deep learning refers to the implementation of artificial neural networks (ANN) with many layers of neurons, where each layer ideally represents higher-level and more abstract features than the previous layer. Inspired by sensory processing of the brain, ANNs learn by optimising weights corresponding to connections between the layered neurons using an algorithm called backpropagation, which works by iteratively making small changes to each weight in a direction which improves performance during training. Deep learning is being implemented effectively in other areas of cardiology such as diagnosis of aortic stenosis(37), heart failure (38,39) and paroxysmal atrial fibrillation from an ECG in sinus rhythm (40); in imaging for speckle-tracking to differentiate physiologic hypertrophy from HCM (41) and even the detection of coronary artery disease from facial photos (42). Similarly deep learning is being used for risk stratification in automated coronary calcium scoring from non-gated chest computed tomography (43) and in utilising routine collected data for cardiovascular risk stratification by evaluating microcalcification on breast screening mammograms (44). It would therefore not be unreasonable to hypothesise careful selection of features from both established and novel complex data sources containing signals for SCD could be the key to unlocking the philosopher's stone of arrhythmology. Indeed, two studies are in recruitment that aim to develop ANNs for SCD prediction (45,46). Where classification models are built with high degrees of

accuracy, SCD prediction deep learning models can transition from "if" (classification models) to "when" (time-to-event analyses(47,48)) to create targeted ICD implantation strategies for individual patients. Significant barriers do however exist for deep learning models to be implemented as continuous, reliable clinical decision tools including algorithmic biases in overfitting, sociodemographic biases within datasets, interpretability and perceived brittleness in not generalising to populations and data outside training data (49). In some cases the brittleness has been shown to be fundamentally unavoidable in the presence of arbitrarily small data perturbations and cannot be overcome by better training or larger volumes of clean data (50).

Practical considerations

Adherence to reporting guidelines designed specifically for diagnostic test accuracy and risk prediction machine learning studies, currently under development(15), in conjunction with evolving consensus best practice guidance(30)(51), will improve the quality of reporting within the field. Included within these should be a requirement to publish training and validation sub-cohort variable, and outcome, distributions as well as their performance metrics concurrently to improve transparency and replicability. Similarly, code and data should be shared where possible to facilitate collaboration, and external validation (52). Whilst *a priori* planning with machine learning models is more difficult than traditional model analyses, we would encourage the techniques for accounting for overfitting and data imbalance to be included early within study protocols and performance measures must be presented by F1 score because of the imbalance inherent to the study of SCD.

Strengths and limitations

This is the first study to collate and summarise the research in using machine learning to predict SCD. The reviewers' diverse domain expertise in bioengineering, computer science,

artificial intelligence and cardiology provide the unique lens through which the literature is required to be appraised. The study is limited by the small number of heterogeneous cohorts, methods and outcomes preventing meta-analysis and the derivation of point estimates to determine the effectiveness of machine learning to predict SCD to date. With time this may not be the case and we look forward to updating this review in the future.

Conclusion

This systematic review shows machine learning for SCD prediction has been under applied and incorrectly implemented but is ripe for future investigation. These first papers should be praised as taking the brave first few steps in paving the way for future work. They appear to suggest machine learning may have some incremental utility in predicting sudden cardiac death over traditional models and may be better suited to amalgamate complex multidimensional data sources that confer risk than traditional models alone. The development and adherence to reporting standards designed for machine learning should improve the quality of evidence reporting in this field.

Acknowledgements

Keith Nockels for his assistance in translating search terms

Funding

JB has a National Institute of Heath Research (NIHR) Academic Clinical Fellowship, SK is an employee of Ufonia, JM is an employee of Faculty AI. GAN is supported by a British Heart Foundation Programme Grant (RG/17/3/32774) and NIHR Leicester Biomedical Research Centre. XL, WBN and GAN are supported by a Medical Research Council Biomedical Catalyst Developmental Pathway Funding Scheme (MR/S037306/1).

Conflict of interest

None declared

Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

Contributorship statement

JB conceived the project with GAN. CP wrote the search strategy. JB, XL, SK, AM, DK were all involved in the review process as specified in methods. JB was primary author of the work with all authors providing revisions to the manuscript.

References

1. Priori S, Blomström-Lundqvist C, Mazzanti A, Blom N, Borggrefe M, Camm J et al. 2015 ESC Guidelines for the management of patients with ventricular arrhythmias and the prevention of sudden cardiac death. European Heart Journal. 2015;36(41):2793-2867.
2. Myerburg RJ, Kessler KM, Castellanos A. Sudden cardiac death. Structure, function, and time-dependence of risk. Circulation. 1992 Jan;85(1 Suppl):I2-10. PMID: 1728501.
3. Moss A, Zareba W, Hall W, Klein H, Wilber D, Cannom D et al. Prophylactic Implantation of a Defibrillator in Patients with Myocardial Infarction and Reduced Ejection Fraction. New England Journal of Medicine. 2002;346(12):877-883.
4. Bardy G, Lee K, Mark D, Poole J, Packer D, Boineau R et al. Amiodarone or an Implantable Cardioverter–Defibrillator for Congestive Heart Failure. New England Journal of Medicine. 2005;352(3):225-237.
5. Merchant F, Levy W, Kramer D. Time to Shock the System: Moving Beyond the Current Paradigm for Primary Prevention Implantable Cardioverter- Defibrillator Use. Journal of the American Heart Association. 2020;9(5).
6. THIJSSEN J, VAN DEN AKKER VAN MARLE M, BORLEFFS C, VAN REES J, DE BIE M, VAN DER VELDE E et al. Cost-Effectiveness of Primary Prevention Implantable Cardioverter Defibrillator Treatment: Data from a Large Clinical Registry. Pacing and Clinical Electrophysiology. 2013;37(1):25-34.
7. Koller M, Schaer B, Wolbers M, Sticherling C, Bucher H, Osswald S. Death Without Prior Appropriate Implantable Cardioverter-Defibrillator Therapy. Circulation. 2008;117(15):1918-1926.
8. Fishman G, Chugh S, DiMarco J, Albert C, Anderson M, Bonow R et al. Sudden Cardiac Death Prediction and Prevention. Circulation. 2010;122(22):2335-2348.
9. Deyell M, Krahn A, Goldberger J. Sudden Cardiac Death Risk Stratification. Circulation Research. 2015;116(12):1907-1918.7.

10. Yu K, Beam A, Kohane I. Artificial intelligence in healthcare. Nature Biomedical Engineering. 2018;2(10):719-731.
11. Liu X, Faes L, Kale A, Wagner S, Fu D, Bruynseels A et al. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. The Lancet Digital Health. 2019;1(6):e271-e297.
12. Hannun A, Rajpurkar P, Haghpanahi M, Tison G, Bourn C, Turakhia M et al. Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nature Medicine. 2019;25(1):65-69.
13. Attia Z, Noseworthy P, Lopez-Jimenez F, Asirvatham S, Deshmukh A, Gersh B et al. An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction. The Lancet. 2019;394(10201):861-867.
14. McInnes M, Moher D, Thombs B, McGrath T, Bossuyt P, Clifford T et al. Preferred Reporting Items for a Systematic Review and Meta-analysis of Diagnostic Test Accuracy Studies. JAMA. 2018;319(4):388.
15. Collins G, Dhiman P, Andaur Navarro C, Ma J, Hooft L, Reitsma J et al. Protocol for development of a reporting guideline (TRIPOD-AI) and risk of bias tool (PROBAST-AI) for diagnostic and prognostic prediction model studies based on artificial intelligence. 2021.
16. Collins G, Reitsma J, Altman D, Moons K. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD Statement. BMC Medicine. 2015;13(1):1.
17. Moons K, Wolff R, Riley R, Whiting P, Westwood M, Collins G et al. PROBAST: A Tool to Assess Risk of Bias and Applicability of Prediction Model Studies: Explanation and Elaboration. Annals of Internal Medicine. 2019;170(1):W1.
18. Zoni-Berisso M, Molini D, Viani S, Mela G, Delfino L. Noninvasive prediction of sudden death and sustained ventricular tachycardia after acute myocardial infarction using a neural network algorithm. Italian Heart Journal. 2001;2:612-620.
19. Rodriguez J, Schulz S, Giraldo B, Voss A. Risk Stratification in Idiopathic Dilated Cardiomyopathy Patients Using Cardiovascular Coupling Analysis. Frontiers in Physiology. 2019;10.
20. Lyon A, Ariga R, Mincholé A, Mahmod M, Ormondroyd E, Laguna P et al. Distinct ECG Phenotypes Identified in Hypertrophic Cardiomyopathy Using Machine Learning Associate With Arrhythmic Risk Markers. Frontiers in Physiology. 2018;9.
21. Goldstein B, Chang T, Mitani A, Assimes T, Winkelmayer W. Near-Term Prediction of Sudden Cardiac Death in Older Hemodialysis Patients Using Electronic Health Records. Clinical Journal of the American Society of Nephrology. 2013;9(1):82-91.
22. Okada D, Miller J, Chrispin J, Prakosa A, Trayanova N, Jones S et al. Substrate Spatial Complexity Analysis for the Prediction of Ventricular Arrhythmias in Patients With Ischemic Cardiomyopathy. Circulation: Arrhythmia and Electrophysiology. 2020;13(4).
23. Shakibfar S, Krause O, Lund-Andersen C, Aranda A, Moll J, Andersen T et al . EP Europace. 2018;21(2):268-274.
24. Nakajima K, Nakata T, Doi T, Tada H, Maruyama K. Machine learning-based risk model using 123I-metaiodobenzylguanidine to differentially predict modes of cardiac death in heart failure. Journal of Nuclear Cardiology. 2020;.

25. Lee S, Zhou J, Li K, Leung K, Lakhani I, Liu T et al. Territory-wide cohort study of Brugada syndrome in Hong Kong: predictors of long-term outcomes using random survival forests and non-negative matrix factorisation. Open Heart. 2021;8(1):e001505.
26. Tse G, Zhou J, Lee S, Liu T, Bazoukis G, Mililis P et al. Incorporating Latent Variables Using Nonnegative Matrix Factorization Improves Risk Stratification in Brugada Syndrome. Journal of the American Heart Association. 2020;9(22).
27. Vergara P, Tzou W, Tung R, Brombin C, Nonis A, Vaseghi M et al. Predictive Score for Identifying Survival and Recurrence Risk Profiles in Patients Undergoing Ventricular Tachycardia Ablation. Circulation: Arrhythmia and Electrophysiology. 2018;11(12).
28. Atallah J, Gonzalez Corcia M, Walsh E. Ventricular Arrhythmia and Life-Threatening Events in Patients With Repaired Tetralogy of Fallot. The American Journal of Cardiology. 2020;132:126-132.
29. O'Mahony C, Jichi F, Pavlou M, Monserrat L, Anastasakis A, Rapezzi C et al. A novel clinical risk prediction model for sudden cardiac death in hypertrophic cardiomyopathy (HCM Risk-SCD). European Heart Journal. 2013;35(30):2010-2020.
30. Good Machine Learning Practice for Medical Device Development: Guiding Principles [Internet]. GOV.UK. 2022 [cited 18 May 2022]. Available from: https://www.gov.uk/government/publications/good-machine-learning-practice-for-medical-device-development-guiding-principles/good-machine-learning-practice-for-medical-device-development-guiding-principles
31. Belkin M, Hsu D, Mitra P. Overfitting or perfect fitting? Risk bounds for classification and regression rules that interpolate. Advances in Neural Information Processing Systems. 2018;31.
32. Bartlett P, Long P, Lugosi G, Tsigler A. Benign overfitting in linear regression. Proceedings of the National Academy of Sciences. 2020;117(48):30063-30070.
33. Leevy J, Khoshgoftaar T, Bauder R, Seliya N. A survey on addressing high-class imbalance in big data. Journal of Big Data. 2018;5(1).
34. Oshiro T, Perez P, Baranauskas J. How Many Trees in a Random Forest?. Machine Learning and Data Mining in Pattern Recognition. 2012;:154-168.
35. Bennett K, Campbell C. Support vector machines. ACM SIGKDD Explorations Newsletter. 2000;2(2):1-13.
36. Wang Y, Zhang Y. Nonnegative Matrix Factorization: A Comprehensive Review. IEEE Transactions on Knowledge and Data Engineering. 2013;25(6):1336-1353.
37. Kwon J-M, Lee SY, Jeon K-H, Lee Y, Kim K-H, Park J et al. Deep learning-based algorithm for detecting aortic stenosis using electrocardiography. J Am Heart Assoc 2020;9:e014717.
38. Attia ZI, Kapa S, Lopez-Jimenez F, McKie PM, Ladewig DJ, Satam G et al. Screening for cardiac contractile dysfunction using an artificial intelligence enabled electrocardiogram. Nat Med 2019;25:70–4.
39. Attia ZI, Kapa S, Yao X, Lopez-Jimenez F, Mohan TL, Pellikka PA et al. Prospective validation of a deep learning electrocardiogram algorithm for the detection of left ventricular systolic dysfunction. J Cardiovasc Electrophysiol 2019;30:668–74.
40. Attia ZI, Noseworthy PA, Lopez-Jimenez F, Asirvatham SJ, Deshmukh AJ, Gersh BJ et al. An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction. Lancet 2019;394:861–7.

41. Narula S, Shameer K, Salem Omar AM, Dudley JT, Sengupta PP. Machine-learning algorithms to automate morphological and functional assessments in 2D echocardiography. J Am Coll Cardiol 2016;68:2287–95.
42. Lin S, Li Z, Fu B, Chen S, Li X, Wang Y et al. Feasibility of using deep learning to detect coronary artery disease based on facial photo. European Heart Journal. 2020;41(46):4400-4411.
43. Zeleznik R, Foldyna B, Eslami P, Weiss J, Alexander I, Taron J et al. Deep convolutional neural networks to predict cardiovascular risk from computed tomography. Nature Communications. 2021;12(1).
44. Huang Z, Xiao J, Xie Y, Hu Y, Zhang S, Li X et al. The correlation of deep learning-based CAD-RADS evaluated by coronary computed tomography angiography with breast arterial calcification on mammography. Scientific Reports. 2020;10(1).
45. Meng F, Zhang Z, Hou X, Qian Z, Wang Y, Chen Y et al. Machine learning for prediction of sudden cardiac death in heart failure patients with low left ventricular ejection fraction: study protocol for a retroprospective multicentre registry in China. 2021.
46. van Dongen LH, Harms PP, Hoogendoorn M, et al. Discovery of predictors of sudden cardiac arrest in diabetes: rationale and outline of the RESCUED (REcognition of Sudden Cardiac arrest vUlnErability in Diabetes) project. Open Heart 2021;8:e001554. doi:10.1136/ openhrt-2020-001554
47. Leger S, Zwanenburg A, Pilz K, Lohaus F, Linge A, Zöphel K et al. A comparative study of machine learning methods for time-to-event survival data for radiomics risk modelling. Scientific Reports. 2017;7(1).
48. 9. Linden A, Yarnold P. Modeling time-to-event (survival) data using classification tree analysis. Journal of Evaluation in Clinical Practice. 2017;23(6):1299-1308.
49. Kelly C, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. BMC Medicine. 2019;17(1).
50. Bastounis, A., Hansen, A.C. and Vlačić, V., 2021. The mathematics of adversarial attacks in AI--Why deep learning is unstable despite the existence of stable neural networks. *arXiv preprint arXiv:2109.06098*
51. Stevens L, Mortazavi B, Deo R, Curtis L, Kao D. Recommendations for Reporting Machine Learning Analyses in Clinical Research. Circulation: Cardiovascular Quality and Outcomes. 2020;13(10).
52. Papers with Code - The latest in Machine Learning [Internet]. Paperswithcode.com. 2021 [cited 22 December 2021]. Available from: https://paperswithcode.com/

Figures legends

Figure 1: PRISMA diagram of search strategy for SCD machine learning studies

Figure 2: Performance metrics of 11 machine learning sudden cardiac death papers. Development models refer to models without validation cohorts. * = no AUC or F1 score published.
AUC = Area under the receiver operating characteristic

Figure 3: Adherence to the Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD) for the 11 machine learning sudden cardiac death papers meeting inclusion criteria

Figure 4: Prediction model Risk Of Bias Assessment Tool for the 11 machine learning sudden cardiac death papers meeting inclusion criteria

Table 1 - Overview of studies meeting inclusion criteria. (95% CI) RR= relative risk, HR = hazard ratio, OR = odds ratio, AUC = area under the receiver operating characteristic, ICD =implantable cardioverter defibrillator, SCD= sudden cardiac death, cMRI = cardiac magnetic resonance imaging, HCM = hypertrophic cardiomyopathy, VT = ventricular tachycardia, VF = ventricular fibrillation.

Study type	Study	Design	Data(n)	Outcome(n)	Machine learning model	Machine Learning Performance	Regression performance
Development models	Atalah et al.(28)	Multicenter retrospective case-control study, 288 participants	Demographics, medical and surgical history, ECGs, chest X-ray, ambulatory monitoring or exercise stress test data, echocardiogram or cMRI and electrophysiology study. (n=10)	Suspected or documented sudden death, spontaneous sustained VT and appropriate ICD discharge	Random Forest	Sensitivity 88.4 (79-94%), Specificity 68.1 (65-70%)	-

	Rodriguez et al.(19)	Prospective cohort of 140 participants with non ischaemic cardiomyopathy as part of the German Autonomic Regulation Trial (ART) study	Coupling of heart rate variability and blood pressure variability (n=12)	SCD or survived arrest - definition of SCD not specified , (n=14 or 77 - inconsistent reporting in table 1/table 4)	Laplacian support vector machines	AUC 0.96, Accuracy 0.99.	-
	Lyon et al.(20)	Prospective UK cohort of 123 participants with HCM	ECG,(n=7)	Risk-SCD score, (single SCD event)	Multi-cluster feature selection method followed by density-based clustering	Four HCM phenotypes identified	-
	Okada et al.(22)	Prospective observational US registry from 3 sites with 122 participants with ischaemic cardiomyopathy and left ventricular ejection fraction <35%	Greyscale CMR data	Ventricular arrhythmia, (n=40)	Laplacian support vector machines	AUC 0.72, Accuracy 0.81, Positive predictive value 0.45, Negative predictive value 0.91.	Multivariable logistic regression OR 1.93 (1.27–2.93) p=0.002 per quartile, multivariable cox regression OR 1.52 (1.17–1.98) p =0.002 per quartile.

	Lee et al.(25)	Retrospective territory-wide Brugada cohort in Hong Kong with 516 participants	Brugada type, genetic, SCD, family history, electrophysiolgy study, ECG, Holter data, (n=26)	VT or VF, (n=71 plus 41 at presentation)	Random Forest and non-negative matrix factorisation	F1 score 0.88, Precision 0.87, Recall 0.89.	Multivariable cox regression F1 score 0.74, Precision 0.76, Recall 0.73 HR 24.0 (1.21 to 479, p=0.037)

Developed (trained) and validated models	Zoni-Berisso et al.(18)	Prospective Italian cohort of 404 participants with myocardial infarction (96 development cohort, 308 validation cohort)	Demographics, ischemic heart disease risk factors, thrombotic therapy, clinical course and rhythm disturbances, echocardiograph, radionuclide left ventricular ejection fraction, exercise test, spontaneous ventricular arrhythmias, medical therapy and some selected clinical and electrocardiographic findings, (n=61).	Sudden death, sustained VT, witnessed syncope in patients in whom in the absence of other identifiable causes of syncope, inducible VT, ventricular tachyarrhythmia. (training n=7, validation n=17)	Method of Madansky artificial neural network	Sensitivity 0.96, Specificity 0.93, Positive predictive value 0.46, RR 18	-

	Vergara et al.(27)	Retrospective analysis of 1753 participants undergoing catheter ablation for previous sustained VT (disease agnostic) from 12 international sites making up the International VT Ablation Center Collaborative Group (1251 development cohort, 502 validation cohort)	Sex, age, hyperlipidemia, hypertension, diabetes mellitus, atrial fibrillation, chronic kidney disease, New York Heart Association Functional Classification, type of cardiomyopathy, left ventricular ejection fraction, use of ≥2 antiarrhythmic drugs, type of cardiac device already implanted before the ablation, previous ICD shocks, ES, occurrence of a previous VT ablation (n=15)	VT recurrence, (training n=323, validation n=141)	Random Forest	AUC 0.84, HR 5.2	PAINSED score derived from multivariable logistic regression AUC 0.71

	Goldstein et al. (21)	Retrospective cohort of a US national for-profit dialysis provider comprising of 22 million dialysis sessions (1766 sessions in development cohort and 1628 sessions in validation cohort)	Demographics, dialysis-specific factors, laboratory values, biometric factors, treatments and hemodynamic factors, (n=72).	SCD coded in electronic health record, (training n=883, validation n=814)	Random forest, regularized regression (LASSO), nearest neighbors, and classification and regression tree	Random forest AUC 0.81, Positive predictive value 0.0004	Logistic regression AUC 0.68

	Shakibfar et al.(23)	Retrospective analysis of 19,935 participants with Medtronic ICDs (15,948 in development cohort, 3987 validation cohort)	ICD specific variables, (n=9)	Electrical storm(ES) defined as three or more distinct episodes of VT/VF in 24hours, (n =2367 ES events in 1410 participants- unclear distribution in test and validation cohorts)	Random forest	AUC 0.8, Accuracy 0.96	Logistic regression AUC 0.75, Accuracy 0.96

	Nakajima et al.(24)	Retrospective cohort of 526 chronic heart failure participants across four participating hospitals in Japan (Mean left ventricular ejection fraction 38%)	Cardiac heart mediastinal ratio and washout rate, age, NYHA functional class, left ventricular ejection fraction, laboratory measures, (n=8)	Witnessed cardiac arrest and death within 1 hour of onset of symptoms or unexpected death in patients known well within 24hours plus appropriate ICD discharge or anti-arrhythmic pacing. (training n=27, validation n=10)	Random forest (RF), gradient boosted tree, support vector machine, naïve bayes, nearest neighbors	RF AUC 0.71	Logistic regression AUC 0.73
	Tse et al.(26)	Retrospective multicentre international Brugada cohort with 376 participants (149 development cohort, 227 validation cohort)	ECG and demographics, (n=4).	VT/VF. (training n=37, validation number of events unclear)	Non-negative Matrix Factorization	AUC 0.71, Precision 0.71, Recall 0.70, F1 score 0.71.	Logistic regression AUC 0.64.

Table 2- Prediction model study Risk Of Bias Assessment Tool Scores (PROBAST) of machine learning sudden cardiac death studies meeting inclusion criteria "+" indicates low risk of bias/low concern for applicability, "-" high risk of bias/high concern for applicability, "?" unknown risk of bias/unknown concern for applicability

	Risk of Bias				Applicability			Overall	
Author	Participant	Predictors	Outcome	Analysis	Participant	Predictors	Outcome	Applicability	Risk of Bias
Atalah et al. (28)	+	?	?	+	+	+	+	+	?
Rodriguez et al.(19)	+	?	?	-	?	+	+	?	-
Aurore et al.(20)	+	+	+	+	+	+	+	+	+
Okada et al.(22)	+	+	+	+	+	+	+	+	+
Lee et al.(25)	+	?	?	?	+	+	+	+	?
Zoni-Berisso et al.(18)	?	?	?	-	?	+	+	?	-
Vergara et al.(27)	+	?	?	-	?	+	+	?	-
Goldstein et al.(21)	+	?	?	?	?	+	+	?	?
Shakibfar et al.(23)	?	?	?	-	?	+	+	?	-
Nakajima et al.(24)	+	?	?	-	?	+	+	?	-
Tse et al.(26)	?	?	?	?	?	+	?	?	?

Table 3 - Funding organisations and disclosures for each machine learning sudden cardiac death study meeting inclusion criteria

Study	Funding and disclosures
Attalah et al. (28)	Stollery Children's Hospital
Rodriguez et al.(19)	German Federal Ministry for Economic Affairs and Energy, Secretariat of Universities and Research of the Department of Economy and Knowledge of the Government of Catalonia, CERCA Program/Generalitat de Catalunya, Spanish Ministry of Economy, Spanish Ministry of Science, Innovation and Universities.
Aurore et al.(20)	British Heart Foundation, Wellcome Trust, Spain and Grupo Consolidado BSICoS, Oxford NIHR Biomedical Research Centre, European Union's Horizon 2020 research and innovation programme
Okada et al.(22)	National Institutes of Health, National Heart, Lung, and Blood Institute, Leducq Foundation, Johns Hopkins University Discovery Awards Program
Lee et al.(25)	Research Foundation of Major Science and Technology Projects of Tianjin Municipal Science and Technology Bureau
Zoni-Berisso et al.(18)	Unspecified
Vergara et al.(27)	Biosense Webster, St Jude Medical, Stereotaxis, Medtronic, Boston Scientific and St Jude Medical, Brigham and Women's Hospital, National Heart, Lung, and Blood Institute, Biotronik.
Goldstein et al.(21)	Stanford National Institutes of Health, National Center for Research Resources Clinical and Translational Science, National Institute of Diabetes and Digestive and Kidney Diseases, AHA, National Institute of Diabetes and Digestive and Kidney Diseases
Shakibfar et al.(23)	Innovation Fund Denmark
Nakajima et al.(24)	None declared
Tse et al.(26)	None declared

Figure 1

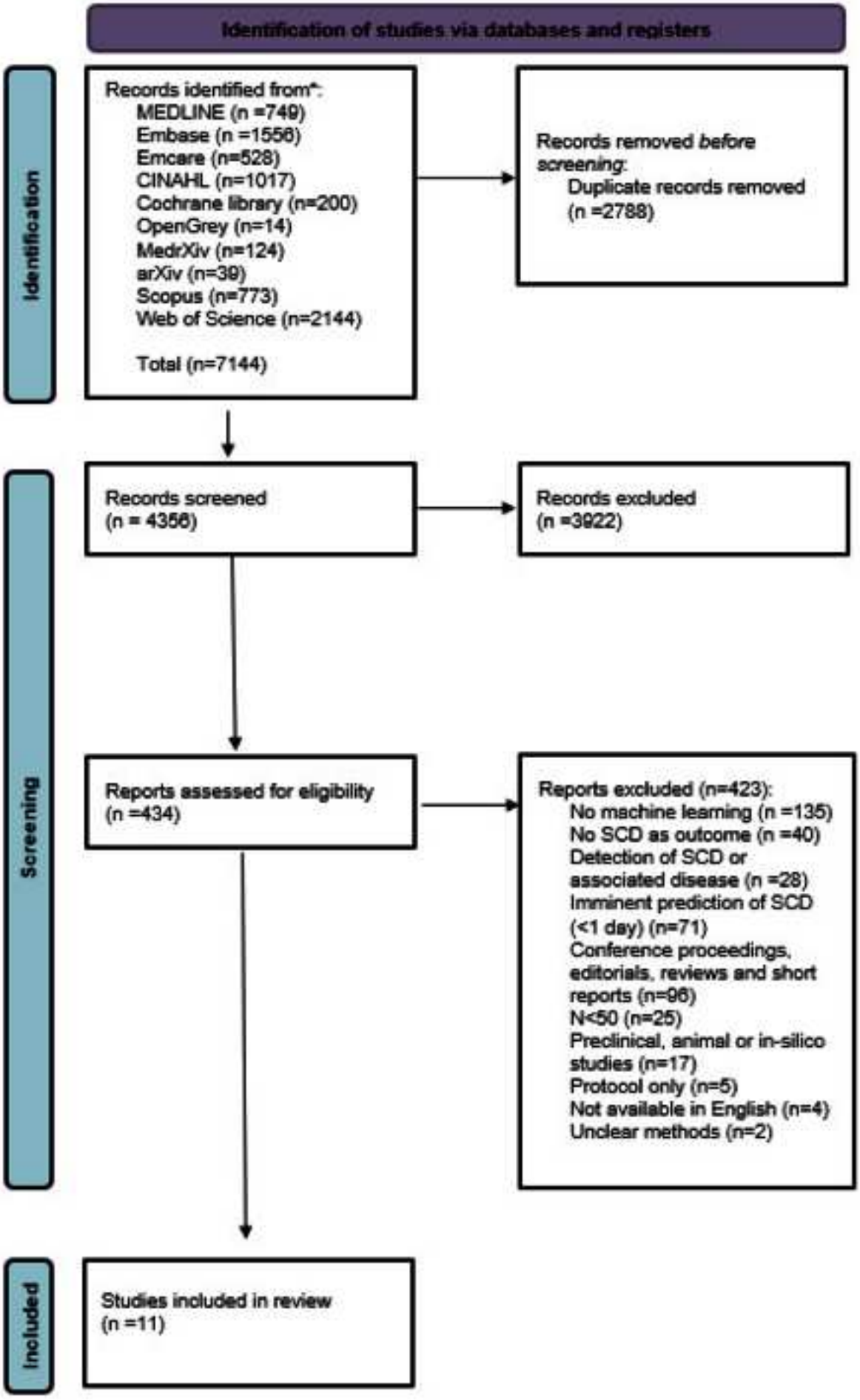


Figure 2

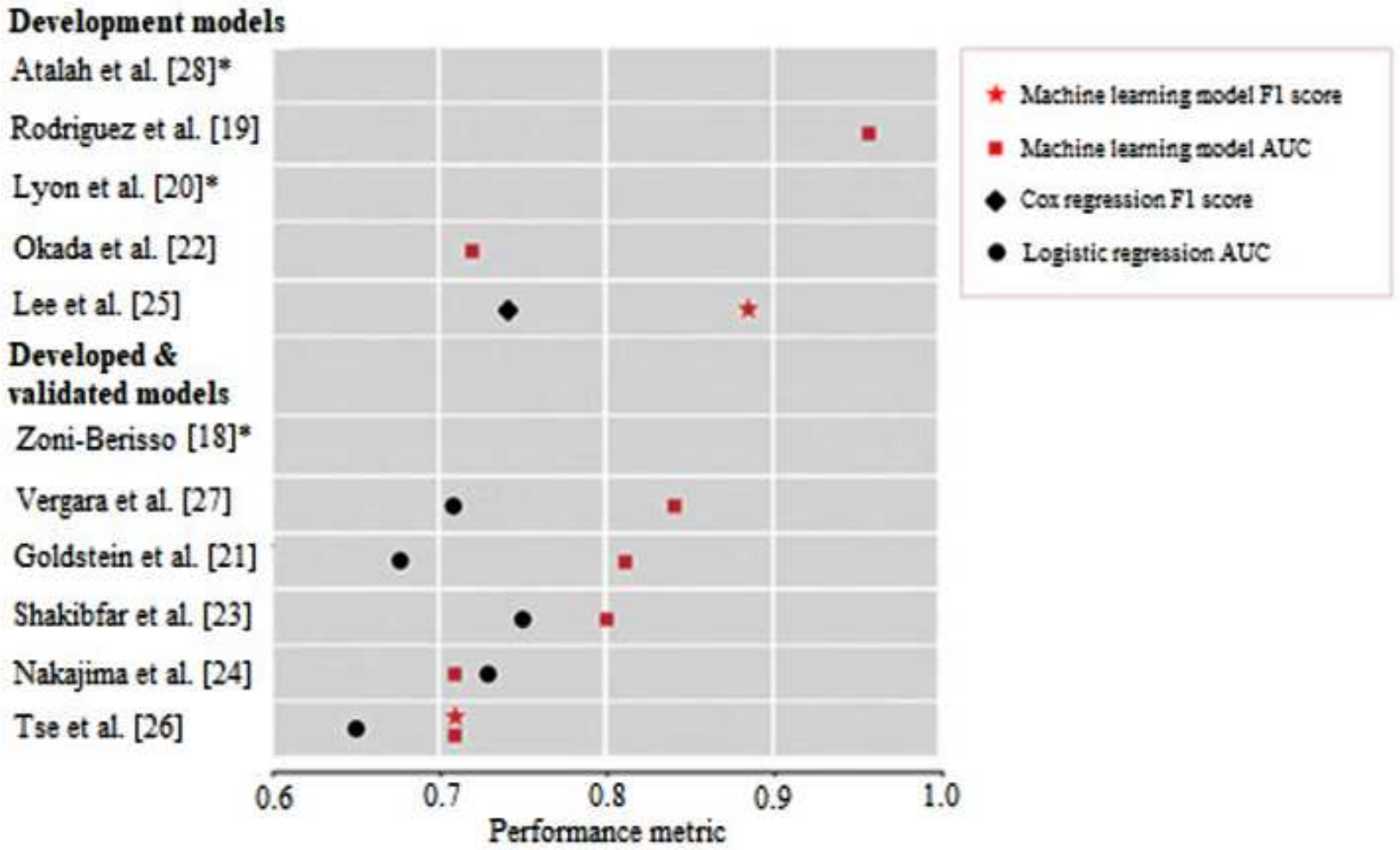


Figure 3

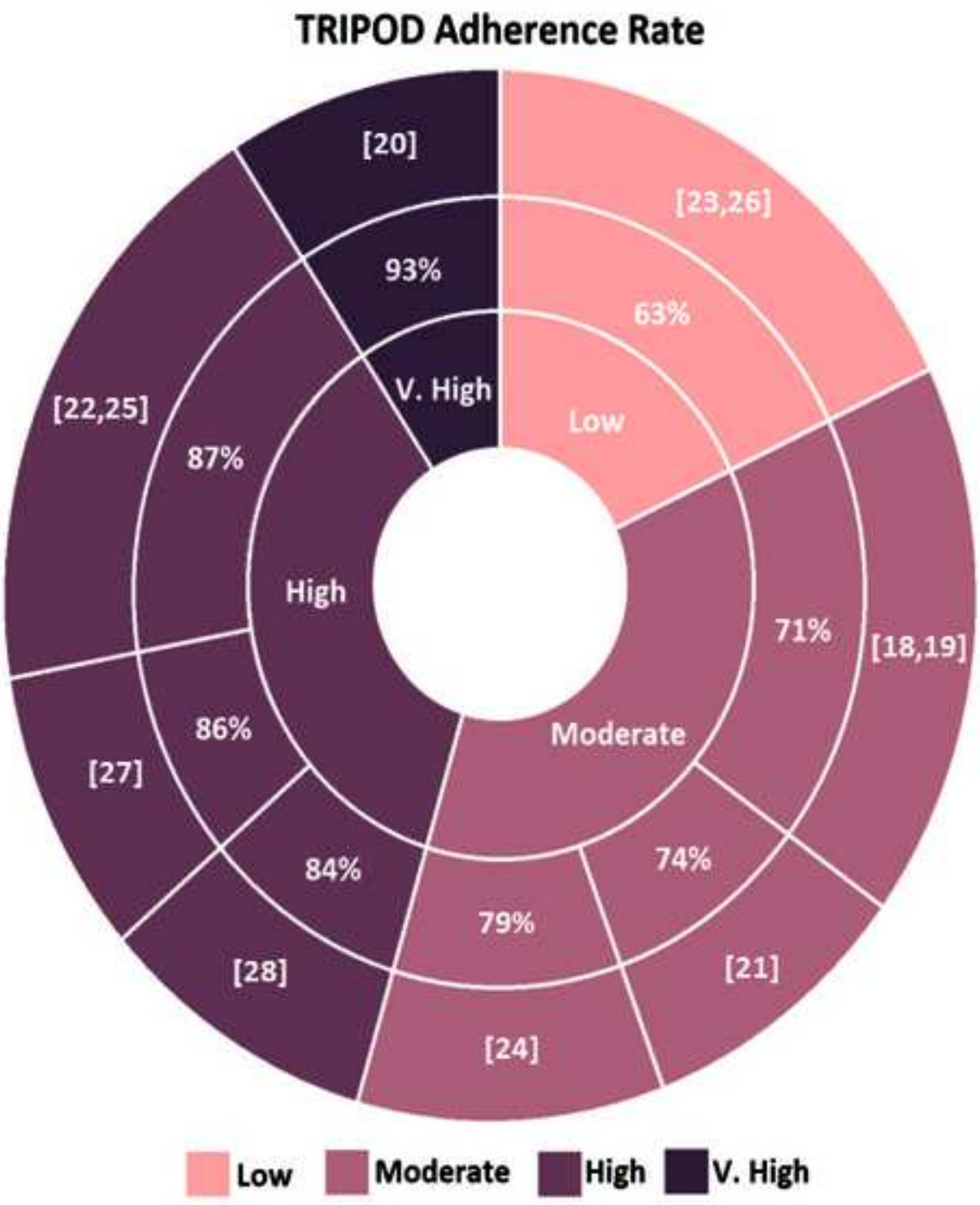
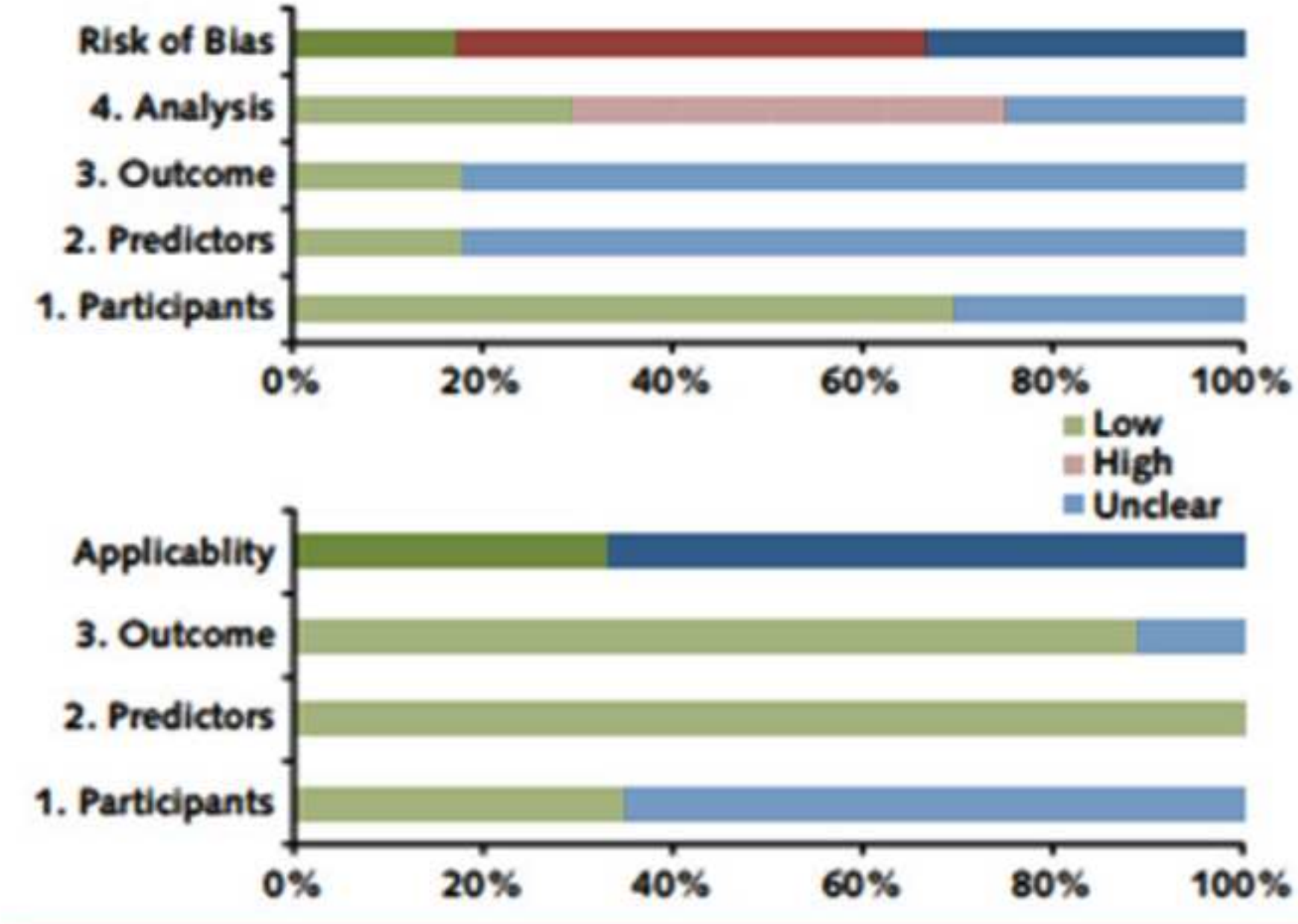


Figure 4



PROBAST – Prediction model Risk Of Bias ASsessment Tool.

PRISMA-DTA Checklist

Section/topic	#	PRISMA-DTA Checklist Item	Reported on page #
TITLE / ABSTRACT			
Title	1	Identify the report as a systematic review (+/- meta-analysis) of diagnostic test accuracy (DTA) studies.	1
Abstract	2	Abstract: See PRISMA-DTA for abstracts.	2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	3
Clinical role of index test	D1	State the scientific and clinical background, including the intended use and clinical role of the index test, and if applicable, the rationale for minimally acceptable test accuracy (or minimum difference in accuracy for comparative design).	3
Objectives	4	Provide an explicit statement of question(s) being addressed in terms of participants, index test(s), and target condition(s).	3
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	4
Eligibility criteria	6	Specify study characteristics (participants, setting, index test(s), reference standard(s), target condition(s), and study design) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	4/5
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	4
Search	8	Present full search strategies for all electronic databases and other sources searched, including any limits used, such that they could be repeated.	Supplement
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	4
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	4
Definitions for data extraction	11	Provide definitions used in data extraction and classifications of target condition(s), index test(s), reference standard(s) and other characteristics (e.g. study design, clinical setting).	5
Risk of bias and applicability	12	Describe methods used for assessing risk of bias in individual studies and concerns regarding the applicability to the review question.	5
Diagnostic accuracy measures	13	State the principal diagnostic accuracy measure(s) reported (e.g. sensitivity, specificity) and state the unit of assessment (e.g. per-patient, per-lesion).	5
Synthesis of results	14	Describe methods of handling data, combining results of studies and describing variability between studies. This could include, but is not limited to: a) handling of multiple definitions of target condition. b) handling of multiple thresholds of test positivity, c) handling multiple index test readers, d) handling of indeterminate test results, e) grouping and comparing tests, f) handling of different reference standards	4

PRISMA-DTA Checklist

Section/topic	#	PRISMA-DTA Checklist Item	Reported on page #
Meta-analysis	D2	Report the statistical methods used for meta-analyses, if performed.	NA
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	NA
RESULTS			
Study selection	17	Provide numbers of studies screened, assessed for eligibility, included in the review (and included in meta-analysis, if applicable) with reasons for exclusions at each stage, ideally with a flow diagram.	6
Study characteristics	18	For each included study provide citations and present key characteristics including: a) participant characteristics (presentation, prior testing), b) clinical setting, c) study design, d) target condition definition, e) index test, f) reference standard, g) sample size, h) funding sources	Table 1,Table 3 6
Risk of bias and applicability	19	Present evaluation of risk of bias and concerns regarding applicability for each study.	Table 2, page 8
Results of individual studies	20	For each analysis in each study (e.g. unique combination of index test, reference standard, and positivity threshold) report 2x2 data (TP, FP, FN, TN) with estimates of diagnostic accuracy and confidence intervals, ideally with a forest or receiver operator characteristic (ROC) plot.	Insufficie nt , table 1
Synthesis of results	21	Describe test accuracy, including variability; if meta-analysis was done, include results and confidence intervals.	Table 1
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression; analysis of index test: failure rates, proportion of inconclusive results, adverse events).	NA
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence.	9-13
Limitations	25	Discuss limitations from included studies (e.g. risk of bias and concerns regarding applicability) and from the review process (e.g. incomplete retrieval of identified research).	13
Conclusions	26	Provide a general interpretation of the results in the context of other evidence. Discuss implications for future research and clinical practice (e.g. the intended use and clinical role of the index test).	13
FUNDING			
Funding	27	For the systematic review, describe the sources of funding and other support and the role of the funders.	14

Adapted From: McInnes MDF, Moher D, Thombs BD, McGrath TA, Bossuyt PM, The PRISMA-DTA Group (2018). Preferred Reporting Items for a Systematic Review and Meta-analysis of Diagnostic Test Accuracy Studies: The PRISMA-DTA Statement. JAMA. 2018 Jan 23;319(4):388-396. doi: 10.1001/jama.2017.19163.

For more information, visit: **www.prisma-statement.org**.

Supplementary material – search strategies

Medline - 749 results on 16th April 2021

---

1 Death, Sudden, Cardiac/ (16059)

2 ("sudden cardiac" adj (death* or arrest*)).mp. (18823)

3 ("sudden heart" adj (death* or arrest*)).mp. (77)

4 (SCD not ("sickle cell disease" or "subjective cognitive decline")).tw,kw. (6812)

5 ((sudden or unexpected) adj ("heart event*" or "cardiac event*")).mp. (89)

6 exp Tachycardia, Ventricular/ (17379)

7 Ventricular Fibrillation/ (17234)

8 (ventricular adj2 (tachycard* or tachyarrhythmi*)).tw. (27553)

9 ventricular fibrillation.tw. (18156)

10 Defibrillators, Implantable/ (17087)

11 exp Cardiac Pacing, Artificial/ (25357)

12 (implant* adj3 defibrillat*).tw. (15991)

13 "implant* cardiac device*".tw. (444)

14 (("implant* cardiac" or ICD) adj3 (fire or firing or pacing or pace*)).tw. (1116)

15 (("anti-tachy" or "anti-tachycard*") adj3 (pace* or pacing)).tw. (174)

16 or/1-15 (108272)

17 risk*.tw,kw. (2394388)

18 predict*.tw,kw. (1691222)

19 probabilit*.tw,kw. (217875)

20 stratif*9.tw,kw. (201076)

21 exp Risk/ (1258350)

22 exp Probability/ (1444153)

23 exp Disease Progression/ (189020)

24 exp Disease Susceptibility/ (174290)

25 exp Cohort Studies/ (2114624)

26 model*.ti,kw. (633179)

27 regression*.tw,kw. (831867)

28 hazard*.tw,kw. (271822)

29 exp Mortality/ (397097)

30 mortalit*.tw,kw. (822226)

31 exp "Sensitivity and Specificity"/ (603630)

32 sensitivity.tw. (840125)

33 specificity.tw. (484127)

34 likelihood.tw. (152422)

35 (ROC adj2 curve*).tw. (41778)

36 AUROC.tw. (4627)

37 or/17-36 (8002793)

38 (machine* adj learn*).tw,kw. (37420)

39 neural network*.tw,kw. (58201)

40 CNN.tw,kw. (6100)

41 RNN.tw,kw. (817)

42 "long short term network*".tw,kw. (3)

43 LTSM.tw,kw. (7)

44 (artificial* adj intelligen*).tw,kw. (11183)

45 machine intelligence.tw,kw. (163)

46 computer intelligence.tw,kw. (17)

47 AI.tw,kw. (29582)

48 computer reasoning.tw,kw. (7)

49 computer vision.tw,kw. (4592)

50 intelligent retrieval.tw,kw. (8)

51 deep learning.tw,kw. (16818)

52 hierarchical learning.tw,kw. (69)

53 transfer learning.tw,kw. (1831)

54 supervised learning.tw,kw. (2990)

55 unsupervised learning.tw,kw. (1561)

56 reinforcement learning.tw,kw. (3765)

57 algorithm*.ti,kw. (42805)

58 support vector machine*.tw,kw. (17611)

59 decision tree*.tw,kw. (9998)

60 random forest*.tw,kw. (10785)

61 k-means.tw,kw. (4573)

62 gradient boost*.tw,kw. (1592)

63 regulari?ation.tw,kw. (7320)

64 (classif*9 adj3 (machine* or computer*)).tw,kw. (7006)

65 (train* adj3 (machine* or computer*)).tw,kw. (4385)

66 (model* adj3 (machine* or computer*)).tw,kw. (23244)

67 transformer*.tw,kw. (2535)

68 encoder*.tw,kw. (2288)

69 decoder*.tw,kw. (1844)

70 TensorFlow.mp. (172)

71 PyTorch.mp. (57)

72 (Torch adj5 ML).af. (0)

73 Keras.mp. (85)

74 Apache Spark.mp. (95)

75 Spark ML.af. (1)

76 "scikit-learn".mp. (53)

77 exp Machine Learning/ (26053)

78 exp Artificial Intelligence/ (110530)

79 or/38-78 (292698)

80 16 and 37 and 79 (799)

81 exp animals/ not humans.sh. (4813301)

82 80 not 81 (749)

****

Embase and Emcare - run 16th April 2021
1556 results in Embase, 528 results in Emcare

---

1 sudden cardiac death/

2 ("sudden cardiac" adj (death* or arrest*)).mp.

3 ("sudden heart" adj (death* or arrest*)).mp.

4 (SCD not ("sickle cell disease" or "subjective cognitive decline")).tw,kw.

5 ((sudden or unexpected) adj ("heart event*" or "cardiac event*")).mp.

6 (ventricular adj2 (tachycard* or tachyarrhythmi*)).tw.

7 ventricular fibrillation.tw.

8 exp heart ventricle tachycardia/

9 exp heart ventricle fibrillation/

10 exp implantable cardioverter defibrillator/

11 exp heart pacing/

12 (implant* adj3 defibrillat*).tw.

13 "implant* cardiac device*".tw.

14 (("implant* cardiac" or ICD) adj3 (fire or firing or pacing or pace*)).tw.

15 (("anti-tachy" or "anti-tachycard*") adj3 (pace* or pacing)).tw.

16 or/1-15

17 risk*.tw,kw.

18 predict*.tw,kw.

19 probabilit*.tw,kw.

20 stratif*9.tw,kw.

21 model*.ti,kw.

22 regression*.tw,kw.

23 hazard*.tw,kw.

24 mortalit*.tw,kw.

25 sensitivity.tw.

26 specificity.tw.

27 likelihood.tw.

28 (ROC adj2 curve*).tw.

29 AUROC.tw.

30 exp risk/

31 probability/

32 disease course/

33 disease exacerbation/
34 general condition deterioration/
35 illness trajectory/
36 disease predisposition/
37 cohort analysis/
38 exp statistical model/
39 hazard ratio/
40 exp mortality/
41 "sensitivity and specificity"/
42 maximum likelihood method/
43 exp area under the curve/
44 or/17-43
45 (machine* adj learn*).tw,kw.
46 neural network*.tw,kw.
47 CNN.tw,kw.
48 RNN.tw,kw.
49 "long short term network*".tw,kw.
50 LTSM.tw,kw.
51 (artificial* adj intelligen*).tw,kw.
52 machine intelligence.tw,kw.
53 computer intelligence.tw,kw.
54 AI.tw,kw.
55 computer reasoning.tw,kw.
56 computer vision.tw,kw.
57 intelligent retrieval.tw,kw.
58 deep learning.tw,kw.
59 hierarchical learning.tw,kw.
60 transfer learning.tw,kw.
61 supervised learning.tw,kw.
62 unsupervised learning.tw,kw.
63 reinforcement learning.tw,kw.
64 algorithm*.ti,kw.
65 support vector machine*.tw,kw.
66 decision tree*.tw,kw.

67 random forest*.tw,kw.

68 "k-means".tw,kw.

69 gradient boost*.tw,kw.

70 regulari?ation.tw,kw.

71 (classif*9 adj3 (machine* or computer*)).tw,kw.

72 (train* adj3 (machine* or computer*)).tw,kw.

73 (model* adj3 (machine* or computer*)).tw,kw.

74 transformer*.tw,kw.

75 encoder*.tw,kw.

76 decoder*.tw,kw.

77 TensorFlow.mp.

78 PyTorch.mp.

79 (Torch adj5 ML).af.

80 Keras.mp.

81 Apache Spark.mp.

82 Spark ML.af.

83 "scikit-learn".mp.

84 exp machine learning/

85 exp artificial intelligence/

86 or/45-85

87 (rat or rats or mouse or mice or swine or porcine or murine or sheep or lambs or pigs or piglets or rabbit or rabbits or cat or cats or dog or dogs or cattle or bovine or monkey or monkeys or trout or marmoset*1).ti. and animal experiment/

88 Animal experiment/ not (human experiment/ or human/)

89 87 or 88

90 16 and 44 and 86

91 90 not 89

****

CINAHL – 1017 results on 16th April 2021

#	Query
S1	(MH "Death, Sudden,Cardiac")
S2	TX "sudden cardiac" N1 (death* or arrest*)
S3	TX "sudden heart" N1 (death* or arrest*)
S4	(SCD not ("sickle cell disease" or "subjective cognitive decline"))
S5	((sudden or unexpected) N1 ("heart event*" or "cardiac event*"))
S6	TI (ventricular N2 (tachycard* or tachyarrhythmi*)) OR AB (ventricular N2 (tachycard* or tachyarrhythmi*))
S7	TI "ventricular fibrillation" OR AB "ventricular fibrillation"
S8	(MH "Tachycardia, Ventricular") OR (MH "Ventricular Fibrillation")
S9	(MH "Defibrillators, Implantable")
S10	(MH "Cardiac Pacing, Artificial+")
S11	TI implant* N3 defibrillat* OR AB implant* N3 defibrillat*
S12	TI "implant* cardiacdevice*" OR AB "implant* cardiac device*"
S13	TI ((("implant* cardiac"or ICD) N3 (fire or firingor pacing or pace*))) OR AB ((("implant* cardiac"or ICD) N3 (fire or firingor pacing or pace*)))
S14	TI ((("anti-tachy" or "anti-tachycard*") N3 (pace* orpacing))) OR AB ((("anti-tachy" or "anti-tachycard*") N3 (pace* orpacing)))
S15	S1 OR S2 OR S3 OR S4OR S5 OR S6 OR S7OR S8 OR S9 OR S10OR S11 OR S12 OR S13OR S14
S16	risk*
S17	predict*
S18	probabilit*
S19	stratif*
S20	model*
S21	regression*
S22	hazard*
S23	mortalit*
S24	sensitivity
S25	specificity
S26	likelihood
S27	ROC N2 curve* OR ROC N2 curve*

S28 TI AUROC OR AB AUROC

S29 (MH "Risk Factors+")

S30 (MH "Data Analysis,Statistical+")

S31 (MH "Probability")

S32 (MH "Prospective Studies+")

S33 (MH "Disease Susceptibility") OR (MH "Disease Exacerbation") OR (MH "Disease Progression+")

S34 (MH "Mortality+")

S35 (MH "Sensitivity andSpecificity")

S36 (MH "ROC Curve")

S37 S16 OR S17 OR S18 ORS19 OR S20 OR S21 OR S22 OR S23 OR S24 OR S25 OR S26 OR S27 ORS28 OR S29 OR S30 OR S31 OR S32 OR S33 OR S34 OR S35 OR S36

S38 (machine* N1 learn*)

S39 neural N1 network*

S40 CNN

S41 RNN

S42 "long short term network*"

S43 LTSM

S44 artificial* N1 intelligen*

S45 "machine intelligence"

S46 "computer intelligence"

S47 AI

S48 "computer reasoning"

S49 "computer vision"

S50 "intelligent retrieval"

S51 "deep learning"

S52 "hierarchical learning"

S53 "transfer learning"

S54 "supervised learning"

S55 "unsupervised learning"

S56 "reinforcement learning"

S57 algorithm*

S58 "support vectormachine*"

S59 "decision tree*"

S60 "random forest*"

S61 "k-means"

S62 "gradient boost*"

S63 regularization

S64 (classif*9 N3 (machine*or computer*))

S65 train* N3 (machine* orcomputer*)

S66 model* N3 (machine* or computer*)

S67 transformer*

S68 encoder*

S69 decoder*

S70 TX TensorFlow

S71 TX PyTorch

S72 TX Torch N5 ML

S73 TX Keras

S74 TX "Apache Spark"

S75 TX "Spark ML"

S76 TX "scikit-learn"

S77 (MH "Machine Learning+") OR (MH "Artificial Intelligence+")

S78 S38 OR S39 OR S40 ORS41 OR S42 OR S43 ORS44 OR S45 OR S46 ORS47 OR S48 OR S49 ORS50 OR S51 OR S52 ORS53 OR S54 OR S55 ORS56 OR S57 OR S58 ORS59 OR S60 OR S61 ORS62 OR S63 OR S64 ORS65 OR S66 OR S67 ORS68 OR S69 OR S70 ORS71 OR S72 OR S73 ORS74 OR S75 OR S76 ORS77

S79 S15 AND S37 AND S78

S80 (MH "Animals+")

S81 (MH "Animal Studies")

S82 TI animal model*

S83 S80 OR S81 OR S82

S84 (MH "Human")

S85 S83 NOT S84

S86 S79 NOT S85

Cochrane strategy – 16th April 2021

Cochrane Database of Systematic Reviews – 12 results

Cochrane Central Register of Randomised Controlled Trials (CENTRAL) – 188 results

ID	Search
#1	MeSH descriptor: [Death, Sudden, Cardiac] explode all trees
#2	"sudden cardiac" NEXT (death* or arrest*)
#3	"sudden heart" NEXT (death* or arrest*)
#4	SCD NOT ("sickle cell disease" or "subjective cognitive decline")
#5	(sudden or unexpected) NEXT ("heart event" or "cardiac event")
#6	(sudden or unexpected) NEXT ("heart events" or "cardiac events")
#7	MeSH descriptor: [Tachycardia, Ventricular] explode all trees
#8	MeSH descriptor: [Ventricular Fibrillation] this term only
#9	(ventricular NEAR/2 (tachycard* or tachyarrhythmi*)):ti,ab
#10	"ventricular fibrillation":ti,ab
#11	MeSH descriptor: [Defibrillators, Implantable] this term only
#12	MeSH descriptor: [Cardiac Pacing, Artificial] explode all trees
#13	(implant* NEAR/3 defibrillat*):ti,ab
#14	(implant* NEXT "cardiac device"):ti,ab
#15	(implant* NEXT "cardiac devices"):ti,ab
#16	(("implant* cardiac" or ICD) NEAR/3 (fire or firing or pacing or pace*)):ti,ab
#17	(("anti-tachy") NEAR/3 (pace* or pacing)):ti,ab
#18	((anti-tachycard*) NEAR/3 (pace* or pacing)):ti,ab
#19	{OR #1-#18}
#20	risk*
#21	predict*
#22	probabilit*
#23	stratif*

#24 MeSH descriptor: [Risk] explode all trees

#25 MeSH descriptor: [Probability] explode all trees

#26 MeSH descriptor: [Disease Progression] explode all trees

#27 MeSH descriptor: [Disease Susceptibility] explode all trees

#28 MeSH descriptor: [Cohort Studies] explode all trees

#29 model*:ti,kw

#30 regression*

#31 hazard*

#32 MeSH descriptor: [Mortality] explode all trees

#33 mortalit*

#34 MeSH descriptor: [Sensitivity and Specificity] explode all trees

#35 sensitivity:ti,ab

#36 specificity:ti,ab

#37 likelihood:ti,ab

#38 (ROC NEAR/2 curve*):ti,ab

#39 AUROC:ti,ab

#40 {OR #20-#39}

#41 machine* NEXT learn*

#42 neural NEXT network*

#43 CNN

#44 RNN

#45 "long short term" NEXT network*

#46 LTSM

#47 artificial* NEXT intelligen*

#48 "machine intelligence"

#49 "computer intelligence"

#50 AI

#51 "computer reasoning"

#52 "computer vision"

#53 "intelligent retrieval"

#54 "deep learning"

#55 "hierarchical learning"

#56 "transfer learning"

#57 "supervised learning"

#58 "unsupervised learning"

#59 "reinforcement learning"

#60 algorithm*:ti,kw

#61 ("support vector" NEXT machine*)

#62 decision NEXT tree*

#63 random NEXT forest*

#64 "k-means"

#65 gradient NEXT boost*

#66 regulari?ation

#67 classif* NEAR/3 (machine* or computer*)

#68 train* NEAR/3 (machine* or computer*)

#69 model* NEAR/3 (machine* or computer*)

#70 transformer*

#71 encoder*

#72 decoder*

#73 TensorFlow

#74 PyTorch

#75 Torch NEAR/5 ML

#76 Keras

#77 "Apache Spark"

#78 "Spark ML"

#79 "scikit-learn"

#80 MeSH descriptor: [Machine Learning] explode all trees

#81 MeSH descriptor: [Artificial Intelligence] explode all trees

#82 {OR #41-#81}

#83 #19 AND #40 AND #82

OpenGrey Search - 14 results on 16th April 2021

("sudden cardiac death" OR "sudden cardiac arrest" OR "sudden heart death" OR "sudden heart arrest" OR SCD OR "ventricular tachycardia" OR "ventricular tachyarrhythmia" OR "ventricular fibrillation" OR ICD OR "implantable cardiac device" OR "implantable cardiac devices" OR "implantable defibrillator" OR "implantable defibrillators") AND ("machine learning" OR algorithm* OR "neural network" OR "neural networks" OR CNN OR RNN OR "long short term network" OR LTSM OR "artificial intelligence" OR AI OR "machine intelligence" OR "computer intelligence" OR "computer reasoning" OR "computer vision" OR "intelligent retrieval" OR "deep learning" OR "hierarchical learning" OR "transfer learning" OR "supervised learning" OR "unsupervised learning" OR "reinforcement learning" OR "support vector machine" OR "decision tree" OR "random forest" OR "k-means" OR "gradient boost" OR regularisation OR regularization OR transformer OR encoder OR decoder OR TensorFlow OR PyTorch OR Torch OR Keras OR "Apache Spark" OR "Spark ML" OR "scikit-learn") AND (risk* OR probabilit* OR predict* OR likelihood* OR stratif* OR regression OR hazard* OR mortalit* OR sensitivity* OR specificity OR AUROC OR ROC)

medrXiv - 124 results on 16th April 2021

"sudden cardiac death" AND "machine learning" in all text

"ventricular fibrillation" AND "machine learning" in all text

"ventricular tachycardia" AND "machine learning" in all text

"ventricular arrhythmia" AND "machine learning" in all text

"ventricular tachyarrhythmia" AND "machine learning" in all text

"cardiac arrest" AND "machine learning" in all text

"implantable cardiac" AND "machine learning" in all text

"cardiac device" AND "machine learning" in all text

"cardiac defibrillator" AND "machine learning" in all text

"implantable defibrillator" AND "machine learning" in all text

"implantable cardioverter defibrillator" AND "machine learning" in all text

"cardiac pacing" AND "machine learning" in all text

"sudden cardiac death" AND "artificial intelligence" in all text

"ventricular fibrillation" AND "artificial intelligence" in all text

"ventricular tachycardia" AND "artificial intelligence" in all text

"ventricular arrhythmia" AND "artificial intelligence" in all text

"ventricular tachyarrhythmia" AND "artificial intelligence" in all text

"cardiac arrest" AND "artificial intelligence" in all text

"implantable cardiac" AND "artificial intelligence" in all text

"cardiac device" AND "artificial intelligence" in all text

"cardiac defibrillator" AND "artificial intelligence" in all text

"implantable defibrillator" AND "artificial intelligence" in all text

"implantable cardioverter defibrillator" AND "artificial intelligence" in all text

"cardiac pacing" AND "artificial intelligence" in all text

Limited to cardiovascular medicine

arXiv - 39 results on 16th April 2021

in all fields:

"sudden cardiac death" OR "cardiac arrest" OR "ventricular fibrillation" OR "ventricular tachycardia" OR "ventricular arrhythmia" OR "ventricular tachyarrhythmia" OR "implantable cardiac" OR "cardiac device" OR "cardiac defibrillator" OR "implantable defibrillator" OR "implantable cardioverter defibrillator" OR "cardiac pacing"

AND

"machine learning" OR "deep learning" OR "transfer learning" OR "supervised learning" OR "unsupervised learning" OR "reinforcement learning" OR "computer vision" OR "artificial intelligence" OR "neural network" OR "neural networks" OR algorithm OR algorithms OR "support vector machine" OR "decision tree" OR "random forest" OR "k-means" OR "gradient boost" OR "machine training" OR transformer OR encoder OR decoder OR PyTorch OR "Apache Spark" OR Keras OR "scikit-learn"

Query: order: -announced_date_first; size: 50; include_cross_list: True; terms: AND all="sudden cardiac death" OR "cardiac arrest" OR "ventricular fibrillation" OR "ventricular tachycardia" OR "ventricular arrhythmia" OR "ventricular tachyarrhythmia" OR "implantable cardiac" OR "cardiac device" OR "cardiac defibrillator" OR "implantable defibrillator" OR "implantable cardioverter defibrillator" OR "cardiac pacing"; AND all="machine learning" OR "deep learning" OR "transfer learning" OR "supervised learning" OR "unsupervised learning" OR "reinforcement learning" OR "computer vision" OR "artificial intelligence" OR "neural network" OR "neural networks" OR algorithm OR algorithms OR "support vector machine" OR "decision tree" OR "random forest" OR "k-means" OR "gradient boost" OR "machine training" OR transformer OR encoder OR decoder OR PyTorch OR "Apache Spark" OR Keras OR "scikit-learn"

Web of Science Advanced Search

2144 results on 26th April 2021

(TS=(Risk* OR Predict* OR Probabilit* OR Stratif* OR (Progress* NEAR/3 disease) OR (Susceptib* NEAR/3 disease) OR Cohort OR cohorts OR Model* OR Regression* OR Hazard* OR Mortalit* OR Sensitivity* OR Specificity* OR Likelihood* OR (ROC NEAR/2 curve) OR Auroc)) AND (TS=((Machine* NEAR/0 learn*) OR "neural network*" OR CNN OR RNN OR "long short term network*" OR LTSN OR (Artificial* NEAR/0 intelligen*) OR "machine intelligence" OR "computer intelligence" OR AI OR "computer reasoning" OR "computer vision" OR "intelligent retrieval" OR "deep learning" OR "hierarchical learning" OR "transfer learning" OR "supervised learning" OR "unsupervised learning" OR "reinforcement learning" OR Algorithm* OR "support vector machine*" OR "decision tree*" OR "random forest*" or k-means OR "gradient boost*" OR regularization OR regularisation OR (Classif* NEAR/3 (machine OR computer*)) OR (Train* NEAR/3 (machine* or computer*)) OR Model* NEAR/3 (machine* OR computer*) OR Transformer* OR Encoder* OR Decoder* OR tensorflow OR pytorch OR (torch NEAR/5 ML) OR keras OR "apache spark" OR "spark ML" OR Scikit-learn)) AND ((TS=("ventricular fibrillation" OR "Artificial cardiac pacing" OR (Implant* NEAR/3 defibrillat*) OR "implant* cardiac device*" OR (("implant* cardiac" OR ICD) NEAR/3 (fire OR firing OR pacing OR pace*)) OR (("anti-tachy" OR "anti-tachycard*") NEAR/3 (pace* OR pacing)))) OR (TS=("sudden cardiac death*" OR "sudden cardiac arrest*" OR "sudden heart death*" OR "sudden heart arrest*" OR (SCD NOT ("sickle cell disease" OR "subjective cognitive decline")) OR ((sudden OR unexpected) NEAR/0 ("heart event*" OR "cardiac event*")) OR (Ventricular NEAR/2 (tachycard* OR tachyarrhythmi*)))))

Scopus (advanced search) - 773 results on 26th April 2021

(TITLE-ABS-KEY(Risk* OR Predict* OR Probabilit* OR Stratif* OR (Progress* W/3 disease) OR (Susceptib* W/3 disease) OR Cohort OR cohorts OR Model* OR Regression* OR Hazard* OR Mortalit* OR Sensitivity* OR Specificity* OR Likelihood* OR (ROC W/2 curve) OR Auroc)) AND (TITLE-ABS-KEY((Machine* W/0 learn*) OR "neural network*" OR CNN OR RNN OR "long short term network*" OR LTSN OR (Artificial* W/0 intelligen*) OR "machine intelligence" OR "computer intelligence" OR AI OR "computer reasoning" OR "computer vision" OR "intelligent retrieval" OR "deep learning" OR "hierarchical learning" OR "transfer learning" OR "supervised learning" OR "unsupervised learning" OR "reinforcement learning" OR Algorithm* OR "support vector machine*" OR "decision tree*" OR "random forest*" or k-means OR "gradient boost*" OR regularization OR regularisation OR (Classif* W/3 (machine OR computer*)) OR (Train* W/3 (machine* or computer*)) OR Model* W/3 (machine* OR computer*) OR Transformer* OR Encoder* OR Decoder* OR tensorflow OR pytorch OR (torch W/5 ML) OR keras OR "apache spark" OR "spark ML" OR Scikit-learn)) AND ((TITLE-ABS-KEY("ventricular fibrillation" OR "Artificial cardiac pacing" OR (Implant* W/3 defibrillat*) OR "implant* cardiac device*" OR (("implant* cardiac" OR ICD) W/3 (fire OR firing OR pacing OR pace*)) OR (("anti-tachy" OR "anti-tachycard*") W/3 (pace* OR pacing)))) OR (TITLE-ABS-KEY("sudden cardiac death*" OR "sudden cardiac arrest*" OR "sudden heart death*" OR "sudden heart arrest*" OR (SCD AND NOT ("sickle cell disease" OR "subjective cognitive decline")) OR ((sudden OR unexpected) W/0 ("heart event*" OR "cardiac event*")) OR (Ventricular W/2 (tachycard* OR tachyarrhythmi*)))))