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Article

Integrating Artificial Intelligence into Cardiovascular Risk Prediction: A Comprehensive Review of Models, Predictors, and Limitations: A Review

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Abstract: The use of artificial intelligence (AI) in cardiovascular disease (CVD) risk prediction has revolutionized preventive cardiology by improving diagnostic precision, early intervention, and health equity. The use of various datasets, including genomic, wearable, imaging, and electronic health records, is highlighted in this paper, which summarizes recent advancements in AI-based risk prediction models for CVD. The construction, creation, and validation of AI models are covered, with a focus on new predictors and how they affect model performance. The paper also examines the differences brought about by algorithmic bias, showing how underrepresentation of particular demographic groups can worsen health inequities and reduce predictive reliability. It is recognized that AI can perform better than conventional statistical models in some situations, especially when it comes to identifying at-risk persons and directing healthcare decisions. Nonetheless, there are still issues with the model's fairness, openness, and generalizability. In conclusion, even though AI has the potential to improve cardiovascular risk assessment and individualized treatment, thorough model evaluation and bias reduction techniques are essential to guaranteeing fair, dependable, and successful clinical application.

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1. Introduction

The Crucially, better cardiovascular treatment can be achieved through the use of digital healthcare data [1]. Artificial intelligence (AI) algorithms can be trained with data from digital devices, such as wearables, applications, intracardiac or mobile devices, diagnostic test results, and electronic health records, to further improve care. With the use of AI, we can potentially find patients who could benefit from early treatments that could change the trajectory of their condition, as well as identify risk factors, forecast illness, and detect early stages of illness [2-4]. Groups that have been historically underrepresented in healthcare receive worse treatment as a result of healthcare disparities and the digital divide, and some groups may be underrepresented or misrepresented in digital datasets [5], [6]. Any step of the process, from creating the research topic to managing data to testing to implementing the model to developing algorithms to conducting clinical procedures after deployment, might be affected by AI bias [7], [8]. Training algorithms on such data can also lead to this outcome. Later cycles of AI learning can amplify these biases and cause therapeutic harm, which could further inequalities among those who are already impacted [9]. The steadily increasing death toll from cardiovascular diseases (CVDs)—from 12.1 million in 1990 to 18.6 million in 2019 [10], has made this health crisis a pressing issue on a global scale. In certain developed countries, risk prediction has revolutionized their approach to combating this global issue, enabling more effective life interventions at a lower cost [11]. Infante et al. and Assadi et al. [13], [13], looked at how important cardiac computed tomography angiography and cardiac magnetic resonance are for predicting AI-CVD. Triantafyllidis et al. conducted a study to examine how deep learning (DL) has impacted the identification, treatment, and management of significant long-term conditions, such as cardiovascular disease [14]. Zhao et al. [15] only recorded social aspects as contributing to AI-CVD prediction.

2. Materials and Methods

Cardiovascular Disease

There are many different CVD risk factors, and the ones used by AI risk prediction systems can differ substantially. Modern AI models take into account a broader array of potential dangers. These might include information obtained from wearable technology (even though it performs worse than conventional data-gathering methods) [16] or the risk of CVD in combination with other medical illnesses like diabetes or cancer [17]. It's crucial to note that AI models can have flaws, including bias (or systematic errors, like in model selection, training data, or model evaluation, present in model predictions [18] and transparency (ensuring that the public has access to information regarding the model's development and derivation. These issues may impact real-world patient care and outcomes, and their presence or absence could lead to a more or less accurate AI prediction model [19]. There are various cardiovascular disease (CVD) AI risk prediction models accessible at the moment, both for PC and AC settings. These models attempt to forecast cardiovascular disease, events, or mortality by using a battery of commonly available tests in primary care or ambulatory care settings. Example data that could be used to train such AI models includes electrocardiogram (ECG) readings [20] and serum creatinine levels [21], which can contain total cholesterol values.

Healthcare Applications of Artificial Intelligence

AI can enable the creation of new, more accurate models. The definition of artificial intelligence is a machine-based system that can function with different degrees of autonomy, may show adaptability once it is in use, and, for explicit or implicit goals, determines from the input it receives how to produce outputs like predictions, content, recommendations, or decisions that can affect real or virtual surroundings [22]. It has been demonstrated that these contemporary risk prediction models are important for both healthcare and risk prevention in general [23]. In comparison to conventional statistical models, these models have also demonstrated that AI-based models improve clinical prediction in a number of areas, including prognosis, risk assessment, and mortality prediction [24].

Models for predicting risks

The term "statistical models that combine information from several markers" refers to risk prediction models. The data that is entered into risk prediction models is used to generate a prediction of a patient's risk [25]. Only the caliber or number of markers (also referred to as risk variables) incorporated into a model can make it dependable and clinically valuable. Acute renal injury, sepsis [26], and cardiovascular diseases like heart failure and coronary artery disease are among the common conditions that risk prediction models are used to forecast. Nevertheless, there are a few significant problems with these models, include excessively optimistic performance measurements (which could result in models that exhibit poor generalization when new data is introduced) [27], or the appropriate dissemination of the clinical prediction models' variability and risk reliability [28]. In other populations, models might not work as well. For instance, age is frequently taken into consideration, which could lead to younger patients receiving a risk prediction value that is erroneous or reduced.

According to Hassan et al.9, there are nine primary steps in the process of creating a risk prediction model. Creating an objective for the model and specifying its parameters and risk variables are the tasks of steps one and two. Step three involved the researchers choosing a dataset to base their model on. Information on the intended risk factors may originate from a single clinic, a network of clinics, or a database on a national or international scale. Step four is derivation, or model construction, which can be done with machine learning and/or deep learning methods and should be done in conjunction with a programming expert [29]. The fifth stage involves validating the model using both the original dataset and additional datasets. This validation should be done through both internal and external means. An AI model's interpretation, or presentation of processed findings, is the subject of the sixth stage. Bias and other underlying assumptions of the model should be recognized and corrected. Model licensing and maintenance, including adding new data (such as populations or risk factors) to existing models, are the focus of steps seven and eight, respectively. Finally, the risk prediction systems underwent clinical evaluation. This can include "the precision of the model's forecasts; the comprehension and application of these odds by doctors and patients; the anticipated efficacy of further actions or interventions; and compliance with them." Adherence to this nine-step process is critical for the proper development of risk prediction models, as it ensures the programming and implementation of the models with the lowest possible margin of error [29].

3. Results and Discussion

Predictors

All AI-Ms had a median of 21 predictors (range: 5-52,000), but the total number was impossible to quantify due to insufficient data in individual papers. These variables were divided into two categories based on whether T-Ms could address them: traditional factors and newly added ones. Apart from the conventional variables such as age (in 400 models), sex (in 357 models), total cholesterol (in 276 models), and smoking status (266 models), a lot of recently added predictors have surfaced in AI-Ms. These include images from electrocardiograms (ECGs) (n = 84, 17%), figure 1 displays how these imaging methods are spread out, with ultrasounds making up 9% (44 cases), MRI at 4% (18 cases), CT at 2% (12 cases), SNPs at 2% (9 cases), and proteins at 1% (20 cases). Using these newly provided data [30], more study revealed that 135 models (30.96%) were built.

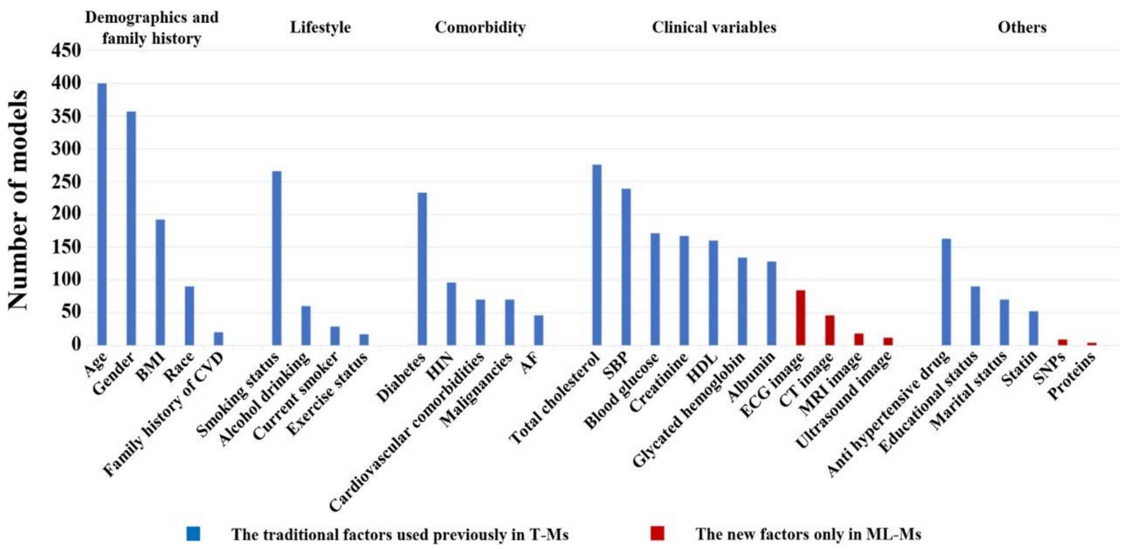

Figure 1. The underlying predictor types of all the models are presented, along with a summary bar chart [30].

Use of predictors for CVD

The included AI risk prediction CVD models were found to use 255 distinct parameters across all models. In the models, age (n=18), BMI (n=13), and smoking status (n=10) were the most commonly used parameters. We found that 57 out of 255 parameters had been used in models in at least two publications, and 27 in at least three, as shown in Figure 2. Furthermore, it's important to note that there are vague predictors, such as "12-lead raw electrocardiogram (ECG) data,"[31], but not the specific components they removed from that data.

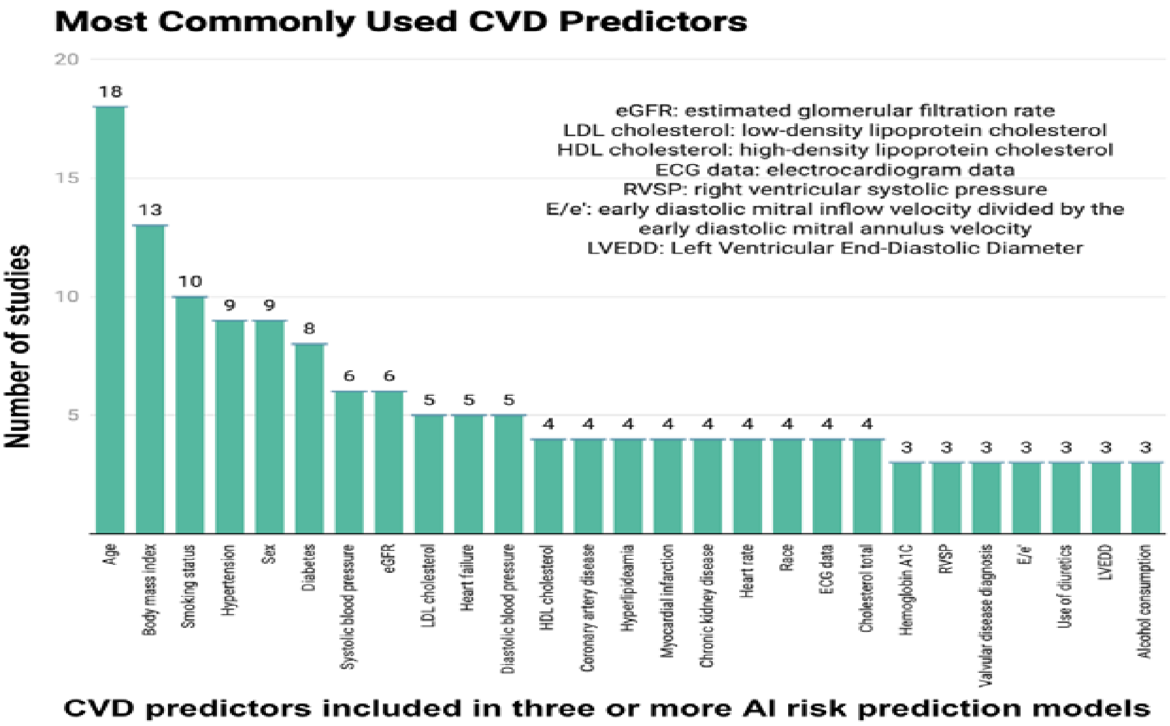

Figure 2. Three or more of the most popular CVD predictors included AI risk prediction model [31].

Cardiac disease results and assessment technique

That the anticipated results from several models varied greatly. We were able to confirm 42 separate ends and 61 combined ends across all models. The two most common outcomes among all 103 were death (n = 16, 16%) and complete cardiovascular disease (n = 40, 39%). However, there was a great deal of disagreement about how to interpret these findings; for instance, cardiovascular disease (CVD) had 19 different interpretations. A diverse range of sources are used to derive definitions, with self-report accounting for 4%, disease codes (ICD9 or ICD10) accounting for 35%, and other international recommendations accounting for 3%. In addition, the outcomes were not defined for 149 models (30.66%) in 21 publications. The most frequent prediction horizons in AI-Ms, which can vary from 1 day to 15 years, were 10 years (n = 107, 22%) and 2.5 years (n = 70, 14%). Only 25 papers detailed the methods used to evaluate all of the outcomes that were considered. These methods primarily comprised surveys, individual interviews, data from national institutes, and healthcare records. While eleven studies claimed to have blinded their readers while measuring results, two explicitly denied using the blinding process [31].

Effects of AI on risk evaluation, cardiovascular disease prediction, and early detection

The prevalence of cardiovascular disease and its associated cardio-metabolic risk factors is disproportionately high in low-income regions, among members of specific ethnic minorities, and in places with inadequate access to healthcare. Healthcare disparities also impact these groups [32]. The risk factors and cumulative exposures that lead to CVDs over a person's lifetime can be addressed by screening and early intervention. Artificial intelligence has the potential to enhance preventative efforts by assisting with early diagnosis, illness prediction, and risk assessment [33]. Artificial intelligence in Figure 3 can facilitate the prediction, identification, and management of cardiovascular disease (CVD) and its risk factors, including obesity, hyperglycemia, dyslipidemia, and hypertension. number 34. One cohort study that looked at 1066 people found that those who used a mobile app that integrated data from wearables, ML, and continuous glucose monitoring had better metabolic health overall. This included things like glycemic levels, variability, and events [4]. Additionally, in research involving multiple centers, a machine learning model that looks at the exposome did better than the Framingham risk score for estimating the risk of cardiovascular disease (CVD), achieving an area under the curve (AUC) of 0.77 compared to 0.65 for the older model. This work provides more evidence that AI systems could outperform more conventional risk assessment methods [35]. Several studies have demonstrated that models based on machine learning (ML) are more effective in predicting the likelihood of incident heart failure (HF) than the present standard HF risk scores [36], [37]. In a cohort study of 8938 adults with dysglycemia21, for example, an ML-based risk score showed superior discrimination and calibration in predicting the 5-year risk of HF than the current HF risk scores (PCP-HF, MESA-HF, and ARIC-HF).

AI can assess the risk of illness and the impact of behavioral changes (like eating or exercising more) on that risk [38]. Furthermore, we can find biomarkers associated with an elevated risk of cardiometabolic disease by training ECG models with artificial intelligence enhancements [39]. Artificial intelligence can assess the cardiometabolic health of the community as a whole and pinpoint populations at increased risk of cardiovascular disease [40]. In essence, AI holds the potential to assist in accurate prognosis and tailored treatments for individuals most at risk of cardiovascular diseases. When it comes to screening for and diagnosing illnesses, AI may help bring about more health equity. A retrospective review of over 17,000 diabetic patients found that Black patients were more likely to comply with their annual testing schedules at primary care centers that used autonomous AI for diabetic retinopathy testing compared to those that did not. Furthermore, subgroups within the community that are already struggling economically have shown greater commitment to AI-deployed sites [41].

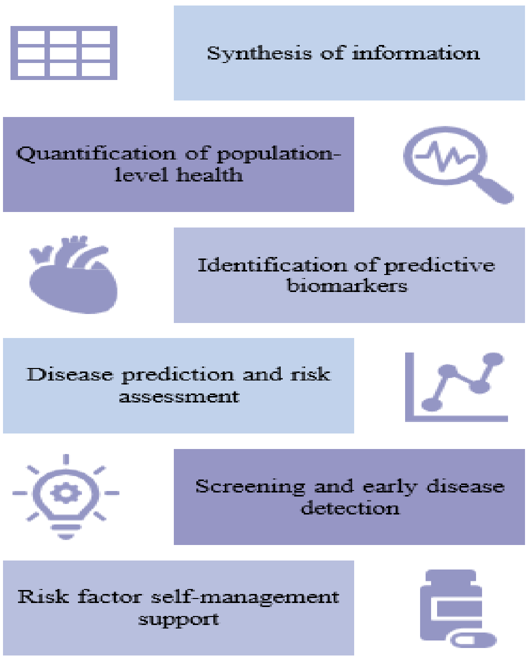

Figure 3. AI-powered cardiovascular disease screening and prognosis.

Reasons why AI bias might make CVD detection and prediction more difficult

Unforeseen consequences that hinder care could arise from bias in AI. Delays or omissions in diagnoses, failure to identify risk factors, or inaccurate risk prediction may occur for certain patient populations. Algorithms can exhibit racist, sexist, or classist tendencies. Cardiovascular disease risk prediction algorithms, for example, could take cues from persistent racial, ethnic, or socioeconomic inequalities in healthcare and incorrectly identify minority and low-income populations [42], [43].

True, AI models may exhibit bias if they perform differently for certain demographic groups. For example, in a study that included 77,163 people who underwent both an echocardiogram and an electrocardiogram (ECG) within a year, researchers looked at how well a deep learning (DL) model for electrocardiograms could detect mitral regurgitation, aortic stenosis, and aortic regurgitation. In terms of quantitative performance, the model was less accurate for older adults (ROC AUC = 0.81 in the 18–60 age group compared to ROC AUC = 0.73 in the 81+ age group) and for black patients (4.4% detection rate) compared to white patients (100 percent detection rate). A similar deep learning model was created to predict heart failure events within 5 years based on ECGs, and its effectiveness was tested using data from 326,518 patient ECGs. As a whole, the model performed better with younger patients (ROC AUC = 0.80) than with older patients (AUC = 0.66). Patient outcomes were worse for Black patients on the model compared to patients of other races; this was particularly evident for younger Black female patients. 109,490 people participated in a study using electronic health records (EHR) to check for bias in machine learning (ML) prediction models for the 10-year risk of coronary heart disease, heart attacks, and strokes, using methods called disparate impact (DI) and equal opportunity difference (EOD). The results indicated that ML models were prejudiced against female patients, as their true positive rates and positive predictive ratios were lower than male patients'. Additionally, their associated EODs and DIs were significantly higher than reference fairness values (EOD = 0, DI = 1), further supporting this bias [44].

We examined another DL model and found significant bias in both gender (EOD = 0.123, DI = 1.502) and race (EOD = 0.111, DI = 1.305). Several de-biasing methods, such as resampling based on sample size and removing protected attributes, failed to significantly lessen bias in ML models. Although resampling by case percentage did decrease bias across gender categories and improve model accuracy, it had no effect on race [45]. Finally, 62,482 patients took part in a study that looked at how well ML's stroke-specific algorithm, the atherosclerotic CVD pooled cohort equation, and other stroke prediction models performed. In all models, as indicated by the concordance index (C-index), Black patients had worse risk discrimination compared to White patients. Black female patients' C-indices in the CoxNet ML model were 0.70, while White female patients' C-indices were 0.75; Black male patients' C-indices were 0.66, while White male patients' were 0.69 [45].

Limitations

A number of limitations must be noted, even though this review offers a thorough summary of the application of artificial intelligence (AI) in cardiovascular disease (CVD) risk assessment. First, it is not possible to directly compare model performance or generalizability due to the heterogeneity among the included studies in terms of model design, data sources, predictor variables, and outcome definitions. It was challenging to evaluate the real-world applicability of many AI models since they lacked external validation and transparent reporting of methodological steps.

Second, a large portion of the review is based on published literature, which may be biased by publication, especially in favor of models with good performance results. Third, given the underrepresentation of some demographic groups, including women, people from low-resource environments, and members of ethnic minorities, the quality and representativeness of training datasets continue to be major concerns. For diverse populations, this lack of inclusivity may result in algorithmic bias and decreased model accuracy. Finally, because AI in healthcare is developing so quickly, it's possible that newer models or methods have surfaced since this review was finished, which could limit how current the results are.

4. Conclusion

With the potential to improve accuracy, customize interventions, and support early prevention strategies, artificial intelligence has emerged as a game-changing tool in the prediction, detection, and management of cardiovascular disease (CVD). The breadth and power of AI-based risk models have been greatly increased by the addition of a variety of predictors, ranging from conventional clinical data to sophisticated imaging and genomic markers. Nevertheless, significant obstacles still exist in spite of these developments. Existing healthcare disparities, especially among underrepresented populations, can be maintained or even made worse by bias in data collection, model development, and implementation. To guarantee clinical reliability and trust, concerns about model validation, generalizability, and transparency must also be addressed. Developing fair, comprehensible, and reliable prediction models under the direction of inclusive data practices and ongoing assessment is the key to maximizing the advantages of AI in cardiovascular care. By doing this, AI can help create more equitable and efficient healthcare systems around the world in addition to supporting better patient outcomes.

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