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AI-Driven Precision Medicine: Unravelling Risk Factors And Enhancing Prevention Of Coronary Heart Disease In Diabetic Patients

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Abstract
Precision Medicine (PM) aims to revolutionize healthcare by promoting individualized approaches to diagnosis, treatment, and predictive assessments. This transformation is made possible through the integration of extensive, multidimensional biological data, which includes genetic profiles, functional biomarkers, and environmental factors. Among chronic conditions, diabetes remains a major global health concern and is closely associated with vascular complications, particularly Coronary Heart Disease (CHD), a leading cause of mortality worldwide. Understanding the contributing factors behind the co-occurrence of diabetes and CHD is crucial for effective prevention and management. Diabetes significantly accelerates both the onset and progression of Cardiovascular Diseases (CVD), making CVD prevention an essential component of diabetes care. In this context, Artificial Intelligence (AI) technologies, particularly Machine Learning (ML) and Deep Learning (DL), have demonstrated exceptional potential in predicting the development of CVD in individuals with diabetes. This study, therefore, aims to identify key risk factors for coronary heart disease (CHD) among diabetic patients and explore AI-driven strategies for early detection and prevention.

Key words: *Coronary Heart Disease, Artificial Intelligence, Cardiovascular Diseases, Precision Medicine, Diabetes.*

1. INTRODUCTION

The term "personalized medicine" (PM) refers to a method of providing healthcare that takes into account each patient's specific traits, such as their genes, way of life, and surroundings, while making decisions and treating them [1]. The first and second are improved therapy efficacy and precision, with fewer side effects and better patient outcomes, which is the main objective of PM. The third is that people who have type 2 diabetes mellitus are disproportionately likely to suffer from cardiovascular disease (CVD) and die from it [2]. Preventing cardiovascular disease is an important part of diabetes therapy since diabetes is linked to an increased risk of CVD, and its progression is facilitated by diabetes [3]. In order to select patients who would benefit most from sodium-glucose co-transporter 2 inhibitors (SGLT2i) and glucagon-like peptide 1 receptor agonists (GLP1-RA) [4], there is a need for better CVD risk prediction in this patient population. This is because these medications lower the incidence of major cardiovascular events in people with diabetes who are at increased risk for CVD.

The scientific statement summarizes the most recent findings about the application of AI algorithms to the study, diagnosis, and management of cardiovascular disease. In addition, it aims to further this objective by examining how digital tools, especially artificial intelligence, might help improve cardiovascular and stroke outcomes through education and implementation science, as well as by providing mechanistic and clinical insights and addressing bias in clinical research.

This article discusses the potential causes of coronary heart disease (CHD) in diabetic persons and offers advice to avoid them.

2. PRECISION MEDICINE WITH AI

The benefits of PM are many. The first benefit is tailoring treatments to each individual's genetic and clinical makeup is the increased likelihood that interventions, drugs, and therapies which have the desired effect [5]. This specific method improves care for patients while reducing the likelihood that scarce resources will be wasted on therapies that won't work or won't help certain people as much as others. Secondly, it can screen for potentially beneficial molecules far more efficiently than a human medical chemist, which helps hasten medication discovery [6]. This expedites the delivery of potentially life-saving pharmaceuticals to the market by streamlining the research process and decreasing drug development timelines. Thirdly, it can reveal which people are more prone to negative drug effects. Precise prescribing and monitoring made possible by this data lessen the likelihood of adverse consequences. And lastly, it's important for cardiovascular intervention [7]. The interventional branch's goal is to identify and treat various cardiovascular diseases using minimally invasive procedures. Interventional cardiology relies on procedures such as percutaneous coronary intervention (PCI) to open blocked or narrowed coronary arteries using stents and balloons, and structural heart interventions such as transcatheter aortic valve replacement (TAVR) to repair structural heart abnormalities [8]. Finally, it provides a glimmer of hope for people dealing with uncommon or otherwise difficult-to-treat medical illnesses.

Precision medicine, which uses PM to target certain genetic mutations, is finding increasing use in cancer treatment, among other fields [9]. Genetic testing for illness risk assessment, personalized vaccines, and regenerative medicine are all fields that are benefiting from its breakthroughs. This innovative approach to healthcare is based on the 8 P's of PM, which stand as a continuation of the 4 P's notion in medicine: predictive, preventative, precise, and participative [10]. A complete framework for PM-based CVD is formed by the following guiding concepts: predictive, preventative, participative, precision, pharmacogenomics, patient empowerment, prognostic, and privacy.

If it is to be effectively integrated into healthcare, it must also overcome a number of obstacles. As PM utilizes a plethora of data types such as genetic information, molecular profiling, laboratory tests, patient histories, lifestyle data, environmental factors that motivate a composite design, and Electronic Health Records (EHRs) the complexity of interpreting and integrating massive volumes of diverse data, also known as "big data," poses a substantial obstacle [11]. Nevertheless, there are logistical and technological hurdles to overcome before these complex data sets can be meaningfully and consistently extracted from their various sources. The initial stage in planning PM is collecting patient data, including genetic information derived from DNA sequencing, blood test biomarker data, and lifestyle data derived from wearables and health monitoring devices [12]. Electronic health records also document treatment outcomes and patients' medical history. For meaningful understanding and accurate forecasting, all of these data sources need to work together.

Revolutionary shifts in the personalized treatment of CVD have been prompted by AI-driven breakthroughs in hardware. The rise in computing power, made possible by innovations like multi-core CPUs, specialized GPUs, and Tensor Processing Units (TPUs), has revolutionized data processing capabilities. Because of these advancements, a wide variety of data modalities, including genetic data, medical imaging, and electronic health records, may be integrated and analyzed, leading to better diagnosis, risk assessment, and tailor-made treatment [13]. Thanks to the proliferation of cloud computing services and the decreasing cost of high-performance computer resources, AI-driven medical solutions are also expanding their reach. Data storage and management innovations, including as scalable cloud storage and high-performance solid-state drives (SSDs), also guarantee the efficient processing of large datasets, or big data, which is essential for personalized CVD supervision [14]. The development of more specialized hardware holds great potential for improving the efficiency and scalability of AI-driven methods, which should lead to better cardiovascular medicine results for patients.

3. PERSONALIZED CARE FOR DIABETICS AND CVD

Diabetes Mellitus (DM) is a condition that usually manifests itself in later years of life. Pancreatic β-cells secrete insulin defectively and insulin resistance, an impairment in insulin-mediated glucose elimination, are the metabolic causes of diabetes. Obesity and lack of physical activity contribute to the development of insulin resistance, which in turn builds on a hereditary predisposition. Although insulin secretion naturally decreases with age, heredity may hasten this process [15]. Other cardiovascular risk factors, such as dyslipidemia, hypertension, and prothrombotic variables, often accompany insulin resistance, which usually occurs before diabetes begins. The metabolic syndrome describes a person's shared pattern of these risk factors. Even in the absence of obvious diabetes mellitus, impaired fasting glucose (IFG) is present in many metabolic syndrome patients. Importantly, the risk factors that make up metabolic syndrome contribute independently to CVD risk; diabetes often develops several years before metabolic syndrome. A new set of approved criteria for diabetes diagnosis was a fasting plasma glucose level of 126 mg/dL is now considered to be the diagnostic cutoff for diabetes, down from 140 mg/dL previously. Just like that, the cutoff for normoglycemia has been lowered from less than 115 to less than 110 mg/dL. Now, IGF is defined as a fasting plasma glucose level between 110 and 125 mg/dL. Due to these modifications, oral glucose tolerance testing is no longer necessary for diabetes diagnosis; now, a diagnosis is based only on verified increases of fasting plasma glucose. And type 2 diabetes and insulin-dependent diabetes mellitus are the new lingo for the same condition. Type 1 diabetes, the other kind of diabetes mellitus, develops when the pancreatic β-cells are immune-mediatedly destroyed [16]. Juvenile diabetes is a term for the onset of type 1 diabetes, which typically occurs in childhood. Microvascular problems, nephropathy, and retinopathy are common in this type of diabetes, and it significantly increases the risk of Coronary Heart Gisease (CHD). This statement will focus on type 2 diabetes rather than type 1 because the latter is far less common. The overarching plan to lower cardiovascular risk will nevertheless account for type 1 diabetes.

Predisposing risk factors include being overweight or obese in the abdomen region, not getting enough exercise, and having a family history of cardiovascular disease. Major risk factors include smoking, high blood pressure, abnormal serum lipids and lipoproteins, and hyperglycemia. The development of a strategy to reduce risk in individuals with diabetes begins with the identification of risk factors. Included in these procedures are taking accurate medical history, doing a comprehensive physical examination, and ordering the necessary laboratory tests. Automated 24-hour ambulatory blood pressure monitoring is one example of a specialized test that might be very helpful. Atherogenic dyslipidemia, also known as diabetic dyslipidemia, is characterized by high triglycerides, tiny LDL, and low HDL cholesterol levels; lipoprotein testing should differentiate between the two. Patients with diabetes should be aggressively treated if their LDL cholesterol levels are even slightly above the threshold of high risk (130 to 159 mg/dL). Hemoglobin A1c levels should be checked periodically to determine the efficacy of glycemic management. In addition, while hyperglycemia is associated with an increased risk of cardiovascular disease (CVD), the presence of additional risk factors such as smoking, high blood pressure, borderline-high-risk LDL cholesterol, and atherogenic dyslipidemia indicates an even higher risk and calls for a more stringent approach to addressing all risk factors.

Predisposing risk factors, such as obesity, physical inactivity, and a family history of early CVD, must be examined in order to complete the risk assessment in diabetes patients. Understanding the relationship between the primary risk factors and their antecedents requires first identifying the elements that put people at risk. An elevated waist circumference, a hallmark of abdominal obesity, is often indicative of insulin resistance. Therapeutic change of lifestyle patterns might begin with a thorough evaluation of the status of the underlying risk factor. Pharmacological management of risk factors may be necessary when a positive family history of cardiovascular disease or diabetes indicates a genetic basis for risk. On top of that, it's not uncommon for a favourable family history to reveal more relatives who could benefit from risk-factor intervention.

4. CURRENT TRENDS IN CVD WITH DIABETICS

Although the incidence of CVD is 2-3 times greater in individuals with DM compared to those without DM globally, studies indicate that the overall prevalence of CVD caused by DM is decreasing globally. Total CVD prevalence in DM varied between 14.3% and 46.9% before to 2016[17], with a meta-analysis spanning 2007–2017 indicating a prevalence of 32%. In 2019, thirteen nations reported a weighted CVD prevalence of 34.8%; however, this figure varied greatly among the nations, ranging from 18.0% in Israel to 56.5% in Saudi Arabia. The prevalence of cardiovascular diseases, stroke, myocardial infarction, peripheral artery disease, and HF all declined with time. Artime et al. found that cardiovascular disease

(CVD) affected 7–41% of Spanish type 2 diabetic patients, and that CVD-related in-hospital deaths occurred at a rate of 6–11% [18].

Concurrent with recent results from South Korea, Sweden, and Ethiopia, DM is associated with a lower risk of CVD. Nonetheless, from 2006 to 2015, the risk of HF rose in the South Korean study [19]. This trend was also seen in patients with a history of hypertension and a duration of DM more than 10 years. The risk of heart failure (HF) increases by 17% for every 5 years that diabetes is present, according to a study that looked at the correlation between the two variables [20].

There has been a 3-5% yearly drop in the rates of CVD since the early 1990s [21], and this trend has been observed among DM patients in high-income nations like the United Kingdom, Sweden, Canada, and the United States. Still, there is a significant disparity between the rates of CV morbidity and mortality in the DM and non-DM populations. Data on the incidence of CVD among patients with DM from middle- and low-income countries, as well as from investigations conducted globally, is unfortunately scarce.

The incidence of death from CVD in DM steadily fell in 2019, in line with the falling trend of CVD incidence overall. The death rates in Sweden decreased by around 20% between 1998 and 2014. Furthermore, from 1990 to 2019, there was a general trend toward a decrease in DM mortality in EU countries. Similarly, during 1988–1994 and 2010–2015, the United States had a decline in both the overall mortality rate and the percentage of fatalities attributable to vascular causes. There was a comparable pattern in South Korea [16] and Hong Kong. There may be a discrepancy between RCTs and real-world data due to the absence of standardized definitions of CVD outcomes (including HF) [23], which would explain why a systematic review of diabetes CV outcome clinical trials found no improvement in CV mortality in DM, contradicting the results of observational studies. Worldwide, low- and middle-income nations had greater estimated CVD death rates among diabetic patients compared to high-income nations [22]. This suggests that, similar to high-income nations, low-income countries may eventually see a decline in the global CVD-related death rate among diabetics.

The total number of deaths globally due to CVDs and DM has increased, along with population expansion and aging, despite a general trend toward lower CVD mortality rates. The incidence and mortality rate of DM, on the other hand, are rising every year [3]. In 2019, the Western Pacific area had the highest number of adult diabetes-related deaths, followed by Southeast Asia. Among patients under 60 years old, Africa had the highest proportion of diabetes-related deaths [23]. Both cardiovascular disease and diabetes pose serious risks to human health; in 2019, they ranked among the world's top ten killers.

The ALTITUDE study found that non-CVD causes were replacing CVD as the leading cause of death in DM [24]. Approximately 46.5% of all fatalities among American adults diagnosed with diabetes occurred due to non-vascular, non-cancer causes between 2010 and 2015. The proportion of mortality caused by cancer remained unchanged from 1988 to 2015 [25]. From 2001 to 2018, the primary cause of death among adults with diabetes in England shifted from vascular causes to cancer. Additionally, there was a decline in cancer and CVD-related mortality among older DM patients in Australia, which obscures the increasing excess risk in younger patients. Some research suggests that diabetes mellitus (DM) that manifests at a younger age may raise the risk of death from cardiovascular disease (CVD) while somewhat lowering the risk of death from cancer. In conclusion, while there have been significant improvements in CVD mortality rates among DM patients, there is a lack of information regarding the primary cause of death among DM patients, particularly those in their early years.

5. PREVENTION FOR CVD WITH DM

Reducing mortality and the economic burden of heart attack and stroke could be achieved by directing efforts toward preventing CVD occurrences in high-risk populations. Lifestyle adjustments, such as quitting smoking, eating properly, and getting more exercise, can regulate blood sugar, blood pressure, and cholesterol, and delay or prevent CVD.

Primary prevention is to keep diabetic people from developing new cardiovascular disease or to delay its onset. It is necessary to diagnose DM in individuals who do not have CVD as soon as possible and to detect CVD-related risk factors in high-risk groups residing in the community as soon as possible. In diabetic patients who already have cardiovascular disease, secondary prevention entails treating risk factors. According to a 2012 position statement by the American Diabetes Association (ADA) and the European Association for the Study of Diabetes (EASD), patient-centered care should be considered when making decisions about secondary prevention for diabetic patients with established CVD. This is in line with the 1999 approval of comprehensive medical intervention for secondary prevention among diabetic patients with clinical CVD [26]. In 2018, the focus shifted from the glucocentric approach to managing CVD in DM to patient-centered care. This shift entailed taking into account the patient's unique medical history, lifestyle choices, and metabolic and cardiovascular risk factors. Achieving precision in medical therapy for patients with diabetes and cardiovascular disease will be a protracted process.

Preventing and treating cardiovascular disease (CVD) in diabetes mellitus (DM) requires an accurate assessment of risk factors. For primary prevention in diabetes mellitus (DM), the American Heart Association (AHA) and the American College of Cardiology (ACC) have created a risk stratification tool called the Risk Estimator Plus. This tool may determine a patient's risk of atherosclerotic CVD over the next decade and give them personalized recommendations based on their age (40–79). Secondary preventive risk categorization is currently being tested in clinical settings [27]. Instead of categorizing patients into primary or secondary prevention groups, the European Society of Cardiology (ESC) suggests that those with pre- or established diabetes should be divided into moderate-, high-, and very high-risk levels for CVD risk stratification according to comorbidities and the duration of the disease. Diabetes care that is tailored to each patient's unique needs is made possible by these three tiers of risk classification.

The criteria used for risk stratification vary slightly between the ESC method and the ACC/AHA method. Age ⊒Y40, sex, blood pressure, blood lipids, history of diabetes, smoking, and drug use are factors that the Risk Estimator Plus takes into consideration, but it does not take into consideration the comorbidities and duration of diabetes, particularly in teenagers as a result of the rise in obesity occurrence. Age ≥ 75 years, diabetes mellitus type 2, hypertension, peripheral artery disease, history of heart failure, history of a previous coronary artery bypass graft, current smoking, and renal dysfunction are all factors that are taken into consideration when stratifying patients for secondary prevention. In addition to taking into consideration comorbidities and the duration of diabetes, the ESC method takes into consideration obesity, renal impairment, left ventricular hypertrophy, and retinopathy instead of a history of CV-related disease. It is based on three levels of risk stratification and acknowledges the complexity of developing CVD. To help patients with diabetes and cardiovascular disease choose the best personalized treatment plan, it would be helpful to compare the risks of using a risk estimator vs a risk stratification tool.

6. CLINICAL PRESENTATION OF CVD WITH AI

Chronic vascular diseases (CVDs) cause a disproportionately high amount of illness and death around the world. Statistics show that cardiovascular disease (CVD) kills more people than any other type of disease on a worldwide scale. It encompasses a range of cardiovascular diseases, such as CAD, HF, PVD, and stroke. Developed and developing nations alike bear the brunt of CVD, although the disease is becoming more common in low- and middle-income nations as a result of urbanization, changes in lifestyle, and an aging population [31].80 Over 17.9 million people die each year from CVD, which is about 31% of all fatalities worldwide, according to the World Health Organization (WHO). In order to tackle this increasing problem, we need global programs for prevention, early detection, effective management, and ongoing research into the myriad of risk factors that contribute to the development of CVD. The risk factors shown include both old-fashioned ones, like people's habits (such as smoking, drinking, and eating fast food), and newer ones, such people's genes and health problems. The breadth of risk assessment is further expanded by the fact that some risk models incorporate environmental considerations [32]. An individual's risk for having CVD can be precisely and holistically assessed through the comprehensive integration of multiple risk variables. These factors are acquired from electronic health records (EHRs), medical imaging, omics data, wearables, and genetic testing.

IMAGING

Clinical decision-making for cardiovascular disorders and stroke now relies heavily on imaging as a diagnostic tool. Image processing, segmentation, quantitation, and interpretation are all responsibilities that specialists frequently feel overwhelmed with, and mastery of these areas requires years of training [33]. There is a severe lack of qualified medical image interpreters, which worsens the health care gap between low- and high-income regions, nations with and without adequate resources, and individuals in underserved communities. There is growing interest in AI/ML-based imaging techniques for cardiovascular disorders and stroke because they address several of these concerns [34].

CHALLENGES OF IMAGING WITH AI

Obtaining, organizing, and distributing data appropriately are three major constraints unique to imaging. In addition to being hard to come by, imaging data stored in clinical repositories is frequently unlabeled and in an unstructured format. When training with labeled data is easy, it's best to use supervised learning; when labeled data is expensive or hard to get, unsupervised learning is the way to go. In order to apply the right AI/ML approach to the given data, it may be necessary to consider additional techniques. These may include weak supervision, which involves applying pretrained models to a new classification task, or a hybrid semisupervised learning approach, which involves using some appropriately labeled data but mostly unlabeled. A newly released 11-point framework/checklist offers advice on how to do things like: formulate a research question; select a suitable ML/deep learning model for each problem type; determine the study design and a priori sample size; specify the nature and type of training, validation, and test datasets; report on the reliability of data labeling and annotations, particularly in reference datasets; and appropriately report results using accepted statistical measures [34].

ELECTROCARDIOGRAPHY

Electrocardiography has already been profoundly impacted by use of AI to the ECG. First, the enormous scalability of human capacities made possible by automated interpretation allows for the interpretation of an ever-increasing volume of electrocardiograms (ECGs). Second, disease phenotyping is improved by AI/ML algorithms because they can detect interconnected nonlinear patterns in the electrocardiogram (ECG) that are generally unnoticed by specialists. Third, these algorithms have the potential to detect hidden disease and foretell future illness, as changes in heart electrical activity might alter it before imaging reveals mechanical or structural abnormalities [35]. Applying AI/ML to the ECG has the potential to uncover new phenotypes by separating subtypes of similar illnesses.

CHALLENGES OF ELECTROCARDIOGRAPHY WITH AI

To tackle uncertainties like automation bias, overfitting (i.e., poor generalizability), and vulnerability to adversarial attacks (i.e., imperceptible data may cause AI/ML misclassification), robust clinical validation in large diverse populations that minimizes bias is essential. Potential factors that could boost acceptance include clinicians' experience with artificial intelligence and machine learning, "stress testing" of electrocardiographic algorithms, and hybrid approaches to model building that integrate data-driven and domain-specific knowledge. Lastly, there may be a lack of resources for developing AI/ML algorithms, such as open-source datasets and digitized, well-labeled electrocardiographic data. Although the area under the curve (AUC) is often used to quantify the success of AI/ML models [36], the best statistical metrics or combination of metrics to evaluate the efficacy of these new types of tests have not been established.

MONITORING IN HOSPITALS

For a long time, monitoring patients while they are in bed has been the norm. When a vital sign goes above a certain level, traditional systems will sound an alarm based on expert static criteria. One reason these systems are only somewhat accurate is because they use a heuristic to assign scores to specific vital signs while neglecting the possibility of correlation between other physiological data [37]. Tools to extract subtle fingerprints among concurrently obtained vital sign signals are made possible by using AI/ML to streaming physiological signals from bedside monitors; this has great potential for improving outcomes.

CHALLENGES OF MONITORING IN HOSPITALS WITH AI

The absence of thorough prospective evaluation is a big problem for existing AI/ML-based monitoring systems. Also, clinical end points like mortality have not been demonstrated to be affected by research, and forecasts that could directly feed clinical decision-making are limited. Despite claims of significant decreases in mortality, the Hawthorne effect which was exposed by the use of algorithms during the COVID-19 pandemic may be at play here [38]. Noise in ambulatory data and the absence of standardized platforms to report predictions to clinicians are two potential practical limitations of AI/ML systems. Some research has found that reliable data is provided for just half of the monitoring period [39]. Adopting best practices for trial protocol design and generating more meaningful time-varying metrics over longer periods of time could be solutions.

WEARABLE TECHNOLOGIES IMPLANTATION

Redefining the boundary between inpatient and outpatient care, novel intervention time points, and unparalleled data on illness development could be made possible by the ability to interpret physiological data on a near-continuous basis. Disparities in care may also be lessened by this technology [40]. The development and validation of realistic care pathways for each patient and illness type that are most susceptible to AI/ML-enabled monitoring remains a significant unresolved subject.

CHALLENGES OF WEARABLE TECHNOLOGIES WITH AI

It is important to consider the form aspect of wearables when evaluating devices, as it impacts signal quality and patient comfort. Since patients own the data, there are unique ethical concerns around the use of AI and ML to mobile device data that must be addressed by all parties involved to ensure data privacy, operability, and integrity. Wearable and implantable technologies in the US that are enabled by AI/ML need to have regulatory procedures established. On the other hand, we need a deeper reservoir of scientific information. We desperately want data collected in the future, clinical trials, and workflow development. For instance, a notable study found that cardiologists could only confirm wearable-diagnosed AF in 34% to 65% of instances, and that more than 90% of warnings did not result in diagnoses that could be clinically acted upon. In terms of openness, a recent poll found that 35% of doctors would be unwilling to utilize wearables powered by artificial intelligence and machine learning in their practice [41], while 11% saw them as "a great danger." The way AF is classified in different AI/ML systems is not uniform. It has still to be seen whether the level of acceptance will increase as both patients and doctors gain experience with the technology.

7. AI-BASED PREDICTIVE MODELS FOR CVD AND DM

Precision medicine uses state-of-the-art technology, including as massive biological databases and High-Performance Computing (HPC), to direct personalized patient diagnoses and treatments [28]. To execute a targeted strategy that can transform healthcare results, these cutting-edge instruments are necessary. Computer algorithms that can find patterns in complicated multidimensional datasets are the backbone of this approach. These algorithms classify binary or multiclass situations using gold standard labels after employing various feature or pattern extraction approaches. Keep in mind that classifier models execute a specific task—risk stratification—to forecast risk or place it into a predetermined bin within the stratified risk framework, while pattern recognition serves as a foundation for feature extraction. Using training characteristics with established gold standard labels, the trained classifier is actually created. Classifiers trained using this data can be either linear or non-linear. Support Vector Machines, Decision Trees, Random Forests, and Artificial Neural Networks are all examples of non-linear classifier models. The algorithms use what they've learned from previous patients with comparable conditions to provide treatment predictions or optimizations for new patients. While NNs and RFs are both non-linear, the huge parameter space of NNs considerably improves their non-linear performance [29]. While RFs rely on a collection of decision trees, each of which adds to a non-linear decision boundary, NNs can learn hierarchical features from data, leading to very complex and non-linear mappings. Surgeons, for instance, can practice procedures in a risk-free environment using 3D models and simulations created by AI. This approach enhances surgical competency by optimizing procedures according to the unique anatomy of each patient [30].

To improve overall outcomes and limit the progression to advanced diseases, early detection, diagnosis, and treatment are crucial for CVDs. Because it provides important insights into vascular health and helps to a comprehensive understanding of cardiovascular disorders, the examination of carotid vessel morphology further enhances the potential of AI. A paradigm change occurred in the area of cardiovascular disease risk assessment with the advent of genomics and artificial intelligence, in response to the increasing worldwide burden of CVD. By revealing vulnerability and biochemical pathways underpinning the disease, genomics provided fresh understanding of the hereditary component of CVD risk. In cases of clinical ambiguity, it can help clarify the diagnosis and pave the way for better treatment choices. The most reliable methods for identifying certain cardiovascular diseases, including dilated cardiomyopathy, aortic stenosis, and ventricular dysfunction, are electrocardiograms (ECGs) and cardiac magnetic resonance imaging (CMRs) [42]. Asymptomatic patients are not the ones who undergo these further tests, but rather those who are suspected of having associated symptoms. Problems with early CVD diagnosis are brought on by the expensive cost of these supplementary instruments, which necessitate specialized knowledge and may not be appropriate as screening tools for the general public. This means that many people go untreated until it is too late, and that advanced illnesses tend to have worse results [43].

In regions where resources are scarce, electrocardiograms (ECGs) are frequently administered because they are easy to administer, inexpensive, and widely available. When it comes to diagnosing CVDs, the ECG has been a reliable tool for quite some time. The amount of experience and competence of the clinician, however, determines how the ECG is interpreted. The raw ECG waveform also has tens of thousands of data points that are hard for doctors to process, which is a constraint that prevents it from being fully utilized [44]. The correlation between ECG features and particular CVDs can be better understood with the use of artificial intelligence (AI) due to its superior processing power, graphic analysis capabilities, and learning capacity [45]. AI can thus pick up on minor but meaningful information from ECG waveforms that doctors miss. We will discuss the most recent developments in applying AI to standard 12-lead ECG for the detection of CVDs.

Prolonged intervals without symptoms are common in valvular heart disorders. The mortality rate, however, spikes sharply once symptoms manifest. Good outcomes are generally achieved by following up with asymptomatic patients and replacing the valve in symptomatic patients. However, it is still difficult to determine how to spot these asymptomatic people. For valvular heart disease, echocardiography is the go-to diagnostic tool, but it's not a good fit for screening purposes. Consequently, there is a lot of interest in whether an AI-enhanced Electrocardiogram (AI-ECG) might be utilized as a screening tool for patients who do not exhibit any symptoms. To identify moderate to severe aortic stenosis (AS) from electrocardiograms, Kwon et al. [46] created a DL-based approach that combines a multilayer perceptron (MLP) and a convolutional neural network (CNN). Internal validation yielded an AUC of 0.88, while external validation yielded an AUC of 0.86, both for recognizing significant AS. According to the results of the sensitivity analysis, the algorithm employed the precordial lead's T wave to identify AS. Curiously, the negative predictive value was greater than 99% at the very sensitive operation point, indicating that this method can be utilized as a screening tool to exclude AS. Numerous individuals have verified this claim. With the use of electrocardiograms and convolutional neural networks (CNNs), Shelly et al. [47] trained a CNN model to detect moderate to severe AS in 129,788 adult patients. With an area under the curve (AUC) of 0.85, an accuracy rate of 74%, and a negative predictive value of 98.9%, AI-ECG did well in the testing group that included 102,926 people. The AUC improved to 0.90 once sex and age were included in the model. Additionally, the AUC for detecting moderate or severe AS, AR, and MR using ECG was 0.88, 0.77, and 0.83, respectively, according to the Valve Net DL model proposed by Elias et al. [48]. The area under the curve (AUC) for all of them combined was 0.84. The algorithm's performance was unaffected by gender, race, or ethnicity, according to subset analyses. A number of studies have shown promise in using AI-ECG as a screening tool for valvular heart disease.

Symptoms and prognosis of atrial fibrillation (AF), particularly paroxysmal AF, can be difficult to pin down. It is possible to miss the diagnosis of atrial fibrillation in patients because they have a typical sinus rhythm when electrocardiograms are taken [49]. But once AF forms, the heart's structure begins to change. Therefore, an extensively trained neural network may be able to detect tiny alterations in normal sinus-rhythm ECGs and use them to forecast AF. To detect atrial fibrillation (AF) in patients with normal sinus rhythm using a conventional 10-second, 12-lead electrocardiogram (ECG), Attia et al. [50] employed a convolutional neural network (CNN). About half a million electrocardiograms were used to train the model. The model's overall accuracy was 79.4 percent, and its area under the curve (AUC) for AF detection from sinus-rhythm ECGs was 0.87 when tested on a test set. Overall accuracy increased to 88.3% and area under the curve (AUC) to 0.90 when tested on all ECGs from the patients' window of interest (31 days before the first recorded AF ECG to that day). Findings demonstrate that this approach is capable of identifying AF patients from ECGs that otherwise display a normal sinus rhythm. Then, in a subsequent study, Khurshid et al. [51] examined three test sets—MGB, BWH, and UK Biobank—to determine the accuracy and correlation of AI-ECG and CHARGE-AF (Cohorts for Heart and Aging Research in Genomic Epidemiology—Atrial Fibrillation) scores in predicting future AF risk. The predictive utility of AI-ECG for CHARGE-AF in AF prediction was demonstrated over a 5-year follow-up period. (MGB, BWH, and UK Biobank respectively had an AUC of 0.823, 0.747, and 0.752, and 0.705 and 0.732). By combining AI-ECG with CHARGE-AF, the model outperformed CHARGE-AF on various prognosticative model criteria, indicating that AI-ECG can be a valuable tool for predicting the likelihood of future AF. Additionally, by evaluating risk factor stratification, AI can detect potential AF. Noseworthy et al. [52] used an artificial intelligence (AI) system to classify 1003 patients with stroke risk factors but normal sinus-rhythm electrocardiograms (ECGs) into two groups: those at high risk and those at low risk. A 30-day ambulatory cardiac rhythm monitor was then provided to all participants for the purpose of detecting AF. The researchers discovered that the incidence of atrial fibrillation was 7.6% in the high-risk group and 1.6% in the low-risk group. Compared to the usual treatment group, the AI-guided screening group had a substantially greater detection rate of AF throughout a median follow-up of 9.9 months, indicating that AI-ECG could potentially identify patients at high risk of future AF. Better outcomes might be possible with more thorough screening of these individuals.

To foretell the occurrence of Coronary Artery Disease (CAD) using SPECT Myocardial Perfusion Imaging (MPI), Betancur et al. [53] attempted to train a DL model. Stress SPECT, MPI, and invasive coronary angiography were conducted by 1,638 patients who did not have CAD within 6 months after MPI. A stratified tenfold cross-validation approach was used to evaluate the model. That DL can aid in the study of MPI and forecast future CAD is demonstrated by the AUC of 0.80 per patient and 0.76 per vessel. Some diseases may be more likely to strike people with certain facial features [54]. Disease screening using these face traits is even possible with DL [56]. With the use of 5796 patient face pictures, Lin et al. [55] trained and validated a DL algorithm that could diagnose CAD. The DL algorithm detected CAD with an accuracy of 68% and an AUC of 0.73 in the testing set, which consisted of 1013 patients.

One important indicator of the function of the left ventricle during systole is the left ventricular ejection fraction (LVEF), which is frequently assessed via echocardiography. A small reduction in left ventricular ejection fraction (LVEF) in the early stages of heart failure (HF) might lead patients to exhibit asymptomatic left ventricular dysfunction (ALVD) over an extended period. Left ventricular systolic function, survival rate, quality of life, and prevention of further deterioration in LVEF and permanent myocardial damage are all much improved if HF patients are able to receive appropriate treatment [57].

On the other hand, asymptomatic patients cannot afford or have an echocardiography. A number of recent studies demonstrated the potential of AI-ECG for ALVD screening. Using electrocardiogram (ECG) and echocardiography data from 44,959 patients, Attia et al. [58] trained a massive neural network to detect cardiac failure (ejection fraction [EF]≤ 35%). An AUC of 0.93 and an accuracy of 85.7% were achieved when the network was tested on a dataset consisting of 52,870 patients. Patients with a positive AI-ECG but negative echocardiography were four times more likely to develop left ventricular dysfunction

(HR=4.1), suggesting that the network can detect both patients with left ventricular dysfunction and abnormal ECG before it manifests, as compared to those who were identified as having a normal EF by both the network and echocardiography (i.e., true negative) during the median follow-up of 3.4 years. In a similar vein, Yao et al. [59] used electrocardiogram data to train an AI model to detect individuals with low EF (EF ≤ 50%). Twelve hundred primary care teams from forty-five different hospitals and 22,641 individuals without HF were randomly allocated to either the intervention or control groups. This study's intervention group used AI-ECG findings. The use of AI-ECG resulted in a 32% improvement in the diagnosis of poor EF within 90 days following the ECG test, as compared to the control group. In addition, the outpatient environment was the most effective in using AI-ECG to enhance low EF diagnosis (OR=1.71), suggesting that AI-ECG could help primary care providers and hospitals in areas with limited resources detect patients with low EF earlier. On the other hand, due to a lack of reliable screening methods for assessing right ventricular function, right heart failure is frequently underreported in clinical settings. On the other hand, left ventricular dysfunction and complete heart failure are intimately associated to right ventricular dysfunction. The availability of a screening and prediction tool for the correct hearing function is critical. To forecast the function of the left and right ventricles from electrocardiogram data, Vaid et al. [60] used a DL model. With an area under the curve (AUC) of 0.84 for detecting right ventricular systolic dysfunction (RVSD) and an AUC of 0.94 for recognizing patients with left ventricular ejection fraction (LVEF) ≤ 40% in both the internal and external databases, AI-ECG clearly demonstrates that the DL model can extract information on biventricular function from ECG. Using AI-ECG, screening for left or right ventricular dysfunction can be more effective.

An often observed etiology of HF associated with diminished LVEF is dilated cardiomyopathy (DC). DC is more common in first-degree relatives of individuals with DC and is more likely to manifest as sudden death in these relatives. This means these loved ones need to schedule echocardiographic exams frequently. However, screening populations without symptoms using echocardiography is not feasible. In order to accomplish early DC diagnosis using ECG, Shrivastava et al. [61] constructed a CNN model. The area under the curve (AUC) for detecting LVEF ≤ 45% using AI-ECG was 0.955, with a negative predictive value of over 99%, in a group of 421 patients with DC and 16,025 participants with normal LVEF. This suggests that AI-ECG could be used to screen for DC and determine if patients need a subsequent echocardiographic diagnosis. While computed magnetic resonance (CMR) is the diagnostic method of choice for left ventricular hypertrophy (LVH) [25], its accessibility and cost make it unsuitable for use in screening for LVH. Using ECGs from 32,239 people, Khurshid et al. [62] built a convolutional neural network (CNN) model to predict left ventricular mass (LVM-AI) as measured by CMR from 12-lead ECG. It appears that LVM-AI may have a reasonable ability to differentiate LVH, as it predicted LVH with AUC of 0.653 and 0.621 when tested in the two separate test sets.

The unexpected demise of a young adult's heart can be caused by hypertrophic cardiomyopathy (HCM). If HCM can be diagnosed early on, sudden cardiac death caused by it can be prevented. Echocardiography can detect HCM, but it is notoriously difficult to utilize on those who have no symptoms at all [63]. Electrocardiogram abnormalities are seen in almost 90% of HCM patients, however they are not disease specific and can be explained by other medical conditions. AI-ECG has the potential to be a useful tool in the diagnosis of HCM. With a sample size of 51,153 healthy individuals who were age-and sex-matched and 2448 patients with HCM, Ko et al. [64] trained and validated an AI-ECG. With an area under the curve (AUC) reaching 0.96 and a sensitivity of 87% and specificity of 90%, our model was able to reliably diagnose HCM using electrocardiogram data in a testing set that comprised 612 patients with HCM and 12,788 control participants. This model's surprising success in young people (those under 40 years old) raises the possibility that AI-ECG could be useful for HCM screening.

Artificial intelligence (AI) offers distinct benefits in echocardiography (ECG), computed tomography (CT), ultrasonography, SPECT myocardial infarction, and many more. DL powered by AI can quickly screen a large number of individuals because it can detect some diseases just by looking at their faces [65].

There is a high rate of postnatal death due to congenital heart disease (CHD), making it the most frequent congenital impairment. In clinical practice, the detection of CHD during pregnancy is generally quite low [67]. This is mainly because there are not enough trained sonographers or important imaging frames that aid in the diagnosis of CHD. In the context of artificial intelligence electrocardiograms (AI-ECG), trained AI models can improve CHD diagnosis by detecting aberrant picture frames that are hard for the clinician to recognize. In a recent study, Arnaout et al. [66] used around 100,000 pictures from screening ultrasounds and echocardiograms taken between 18 and 24 weeks to train a neural network to differentiate between healthy hearts and CHD. The model achieved a negative predictive value of 100% and an AUC of 0.99 in the internal test set, differentiating normal from pathological hearts. Notably, the model demonstrated strong performance even when presented with lower-quality images taken outside of a hospital, indicating that screening ultrasonography using DL technology enhances the ability to detect CHD in foetuses.

8. CONCLUSION

The convergence of Precision Medicine and Artificial Intelligence presents an unprecedented opportunity to revolutionize the prevention and management of Coronary Heart Disease in diabetic patients. AI's ability to analyze vast, complex datasets for personalized risk assessment, early detection, and optimized treatment is demonstrably superior to traditional methods. However, realizing this potential fully requires a concerted, multidisciplinary effort to overcome challenges related to data quality and bias, rigorous validation, ethical considerations, and seamless clinical integration. Prioritizing fairness, transparency, and patient-centered approaches will be crucial to ensure that AI-driven precision medicine truly achieves its promise of more effective, equitable, and individualized healthcare for all.

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