Journal of Drug Discovery and Health Sciences, 2025;2(1):29-36 eISSN- 3048-8842

Journal of Drug Discovery and Health Sciences

journal home page : https://jddhs.com/index.php/jddhs/index

Review Paper

Harnessing Artificial Intelligence & Machine Learning in Treatment of Cardiovascular Disorders: A Review

Yashvardhan Singh[1], Shubham Bhatt[1*], Deepika Gupta[1], Shikhar Verma[1], Prakash Deep[1]

Maharishi School of Pharmaceutical Sciences, MUIT, Lucknow, U.P., 226013, India.

ARTICLE INFO

Article history:
Received: 10 January, 2025
Revised: 18 February, 2025
Accepted: 10 March, 2025
Published: 25 March, 2025

Keywords:
Metamorphosis, Implementations, Personalized cures, Validations, Data Analytics, etc.

DOI:
10.21590/jddhs.02.01.05

ABSTRACT

The advent of AI and ML in healthcare has led to a complete metamorphosis in how we diagnose, treat, and manage CVDs. To illustrate how AI/ML might influence patient benefit and clinical workflow optimization, this review explores the most recent developments and the recent clinical implementations on treating CVD. AI and ML technology assist in risk evaluation, early diagnosis, and personalized cure protocols by employing adept algorithms and data analytics. These include predictive models that can analyze vast amounts of clinical data for patterns and predictive cues that are not readily apparent to human practitioners. These systems further optimize treatment plans and decrease diagnostic error rates. Despite these promising findings, there are still many hurdles before AI/ML can hit clinical primetime. Specific limits mainly concern data privacy, the need for extensive validation studies, and the demand for interdisciplinary work. Beyond heralding the transformative power of AI and ML in cardiovascular medicine, this study calls for a comprehensive approach that considers the legal, ethical, and logistical barriers to tipping the balance in favor of implementing these technologies to enhance patient care. Because cardiovascular diseases (CVDs) continue to be a major cause of death globally, new strategies for better diagnosis, care, and treatment are required. Both machine learning (ML) and artificial intelligence (AI) have become potent instruments for improving clinical decision-making, tailoring treatment, and forecasting the course of diseases. The application of AI and ML in CVDs is examined in this study, with particular attention paid to real-time monitoring via wearable technology, risk stratification using predictive models, and early identification with sophisticated imaging. ML-based drug discovery speeds up the identification of new therapeutic targets, while AI-driven algorithms allow for increased accuracy in the diagnosis of arrhythmias, heart failure, and myocardial infarction. Problems are also covered, such as algorithm openness and data privacy. The use of AI and ML has enormous potential to transform cardiovascular treatment and enhance patient outcomes.

Introduction

Cardiovascular diseases are known to be a leading cause of death in the global perspective. Around 17.9 million deaths worldwide were attributed to CVDs in 2015. Stroke and ischemic heart disease (IHD) were the two primary causes of CVD-related health loss worldwide (Abouelmehdi *et al.*, 2018). CVDs will be responsible for around 22.2 million deaths per year by 2030. Currently, less and middle-income countries account for 75% of fatalities from CVD, which has a 7% impact on GDP (Attia *et al.*, 2021). Fast food and sedentary lifestyles have replaced farming and active lifestyles due to the significant shift in worldwide

***Corresponding Author:** Shubham Bhatt

Address: Maharishi School of Pharmaceutical Sciences, MUIT, Lucknow, U.P., 226013, India.

Email ✉: shubhatt521@gmail.com

Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

population trends over the past few decades. It has been established that a lifestyle that consumes more tobacco reduces the risk factors associated with cardiovascular disorders.

India would lose $237 billion over ten years (2005–2015) in lost productivity and higher healthcare expenditures as a result of the current burden of CVD, according to projections from the World Health Organization (WHO). The high rate of CVD development, high premature mortality, and high case fatality are explained by biological mechanisms, socioeconomic factors, and their interaction. To address this considerable load, it is vital to comprehend the complex processes that underlie the interplay of biological and societal causes (Cheatham & Young, 2000). It is a group of disorders that impacts the hearts and vessels related to it. These are a collection of several diseases, most of which have atherosclerosis as their main cause. Chronic diseases are those that take a long time to manifest symptoms and grow gradually throughout a person's life (Cheung *et al.*, 2000). In Europe, CVDs account for 45% of all deaths, making them very significant for public health. The main causes of CVDs are atherosclerosis, coronary artery disease (CAD), and arterial hypertension. Around the world, atherosclerosis is the leading cause of fatalities from heart disease. It is a maturing condition that causes the artery wall to thicken and harden. It has a huge negative impact on the cardiovascular system and is linked to several ailments. The primary cause of atherosclerosis is high plasma cholesterol (>150 mg/dL). The prevalent cardiac condition known as coronary artery disease (CAD) is characterized by constriction or blockage of the coronary arteries, the primary blood channels (Cho *et al.*, 2022). The main cause of CAD is plaque, which is described as a fatty material that forms inside the intima and is linked to significant inflammation, particularly if the inflammation is continuous. Plaque formation takes place in the vessel wall's intima. This makes it more difficult for the cardiomyocytes to receive enough blood, oxygen, and nutrients. This will cause the breakup of atherosclerotic plaque, leading to thrombosis and vascular closure, ultimately resulting in heart attack, stroke, limb ischemia, or even death. The illness's other causes include low-grade inflammation, lipid accumulation, and a damaged endothelium (Elias *et al.*, 2022).

AH is among the most common CVDs. AH is a substantial risk factor for peripheral vascular disease, heart failure, myocardial infarction, and stroke even if it rarely or never shows symptoms. The most crucial requirements include that a person is diagnosed with an acute heart attack (AH) if their repeated assessment yields a diastolic blood pressure (DBP) of 90 mm Hg and/or a systolic blood pressure (SBP) of 140 mm Hg in the clinic or office. CVDs have a variety of causes. While certain factors—such as age, gender, and genetic makeup—never change, others—such as obesity, dyslipidemia, high blood pressure, smoking, physical inactivity, and bad eating habits—may be reduced or eliminated (Global Atlas on Cardiovascular Disease Prevention and Control, 2011).

Challenges in Treating Cardiovascular Disorders

The objective is to decrease the number of animals utilized in preclinical research studies, improve translation, and facilitate drug discovery by creating a multifunctional platform that combines CADD, constantly developing engineering technologies (such as micro/nanofabrication), and knowledge of the etiology and pathophysiology of CVD. For instance, creating innovative, extremely potent CVD medication options while closely observing toxicity and pharmacokinetics (PK) would be the ultimate objective. Despite the many useful uses of CADD in the development of contemporary medications, these platforms have several limitations. In particular, several lead molecule recantations with CADD have not shown the intended activities in diverse physiological systems, and results in theoretical computer-assisted systems need to be validated in natural systems (Helvaci *et al.*, 2019).

For a chemical to be approved as a definitive lead or treatment, it must meet several prerequisites and certain pharmacological requirements. Only 40% of medication or lead compounds are approved for use in humans after completing many phases of clinical studies. To get around limitations and increase efficacy, it is essential to address the continuous improvements of techniques and algorithms while researching strong lead compounds. To create and maintain high-quality experimental substances, the database's dependability must be increased (Johnson *et al.*, 2018). Because there aren't enough high-quality data sets, many pharmacophoric groupings can't pass the physiological activity test.

However, there are still chances for improvement and optimization. One unmet need is the ability to conduct high-throughput screening for toxicity assessment in drug testing, which would allow for the rapid and cost-effective evaluation of a large number of compounds. The FDA has approved a wide range of drugs in the US, including TKI-related compounds for cancer treatment, which were created using high-throughput screening techniques. Developing a high-throughput drug screening platform that accurately mimics the physiological function of the native cardiac system and produces reliable, consistent results is challenging due to technical limitations and the maturation of the tissue that occurs over time.

The FDA has asked companies to investigate how new drugs affect the human cardiac ether-à-go-go-related (hERG) gene. This gene produces a potassium ion channel in cardiac cells. By studying this, companies can assess the potential heart toxicity of new drugs. Blocking the hERG channel early in the drug development process can prolong action potentials and increase heart toxicity. Researchers also use human-induced pluripotent stem cell-derived cardiomyocytes (hiPSC-CMs) to model various cardiovascular diseases (CVDs) like hypertrophic cardiomyopathy, dilated cardiomyopathy, long QT syndrome, and left ventricular non-compaction (Kilic, 2020).

Furthermore, more precise in-vivo predictions could lead to safer and more successful treatments for CVD patients if in-vitro and in-silico models of the disease are integrated and take into consideration an individual's DNA, environment, and lifestyle choices. The usage of animal models in preclinical research may change as a result of the new paradigm in drug development. They also add to our understanding of diseases by offering fresh perspectives on the underlying biology. To stop the threat posed by a freshly discovered medicine, for instance, the regulatory decision-making paradigm has been altered by the software for anticipating ADMET quality.

Concept of Artificial Intelligence and Machine Learning

The areas of healthcare have experienced tremendous change as a result of technological advancements. The management of information systems in the healthcare sector is connected to specific issues and advancements. In the medical industry, two technologies that are frequently used are big data and business intelligence. Medical intelligence tools and apps include big data and business intelligence, which are employed to practically diagnose and analyze medical issues (Kwon *et al.*, 2020).

Decision support systems are employed in the healthcare industry as well, and they are used to make data-driven decisions. Information is typically handled by data warehouses since handling and processing data is crucial. Data about healthcare systems are usually multifaceted and often analyzed from multiple perspectives for best use. In the healthcare sector, digital dashboards are used in conjunction with methodologies and technologies for data visualization (Libby *et al.*, 2011).

The field of artificial intelligence (AI) is undergoing rapid growth. The development of AI tools and applications should be guided by the requirements and clinical challenges. It's important to use the technology in a manner that improves clinical procedures, considering the impact of diseases and medical issues on technology development. Extensive research has been conducted on the application of AI in healthcare. According to reports, AI is currently being employed to cure a variety of diseases. Heart disease and cancer are two examples of these illnesses (Manzoor, 2016).

There are several examples of AI being used in the healthcare sector. Machine learning (ML) in the medical sciences is the first; it looks at structured data. These could include genetic information, medical records, and the like. Data warehouses are employed to make integration between different kinds of databases easier. Business intelligence is a major factor in the importance of operational databases, which are further classified into many categories for healthcare systems and companies. Systems using artificial intelligence (AI) have used in oncology and can aid in cancer diagnosis.

Individuals who are quadriplegic might benefit from this. In upper-limb prosthetics, artificial intelligence (AI) can be utilized to monitor and regulate the spinal motor neurons. Cardiology is one area that stands to benefit from the application and use of AI technologies. Artificial Intelligence utilizing cardiac imaging can identify cardiac illnesses and conditions. Cardiac MRI image analysis can be used to identify certain medical conditions. In the medical field, accurate diagnosis and treatment are crucial. Patients with severe illnesses might not make it through a postponed diagnosis. It is therefore essential that the diagnosis be finished as quickly as feasible (Narula, 2019).

The use of machine learning techniques may be advantageous for stroke victims. Strokes can be identified using a well-defined process that begins with the monitoring of human activity and progresses to the detection of stroke onset. Patients are able to monitor their own movements (as shown in fig. 1), and any changes from the usual could be an indication or reminder of an impending stroke. Wearable Internet of Things devices can potentially be used to collect patient data. These data, along with their analysis, can be used to forecast strokes. During the process of acquiring and modeling data, a Markov model might be useful. Modeling can also be done with support vector machines (Roth *et al.*, 2017).

Diagnosis & Imaging in CVD

A branch of computer science called artificial intelligence (AI) is a new technical science that imitates and expands human intelligence to tackle challenging issues. Because

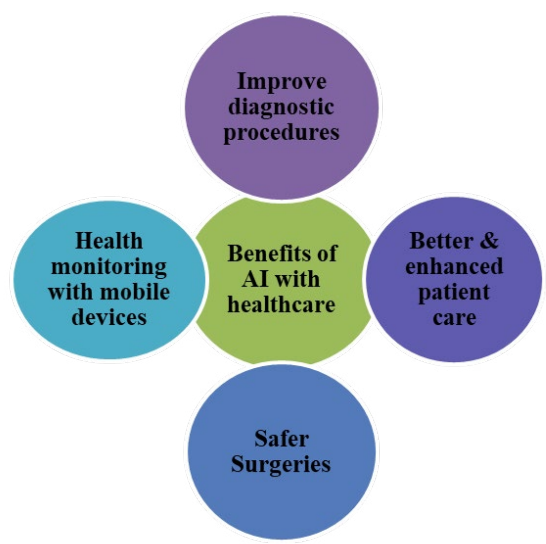

Figure 1: Benefits of AI in healthcare

AI processes data in a way that is comparable to the human brain, it is extremely important in the medical field. Large amounts of healthcare data, such as prescription medication information, ultrasound pictures, medical records, and experimental results, can be recognized, processed, integrated, and analyzed by it. For example, AI-processed echocardiograms (ECGs) are currently utilized to identify heart failure, atrial fibrillation, anemia, hypertrophic cardiomyopathy, and pulmonary hypertension. Clinicians can apply the results of specialized algorithms to existing huge data to improve diagnosis (Savoji *et al.*, 2019).

AI is based on machine learning, which does not require human encoding to find minute patterns in a batch of data. Consequently, these nuanced findings may completely alter the course of human diseases in terms of prognosis, diagnosis, recovery, and prediction. In general, artificial intelligence's machine learning field is more popular. Depending on whether external supervision was given during training, it can be categorized as reinforcement learning, unsupervised learning, or supervised learning (Schneider, 2010).

Lowering the rate at which the illnesses evolve to more severe forms and improving overall outcomes are dependent on early detection, diagnosis, and treatment of CVDs. When it comes to identifying certain CVDs, like ventricular failure, aortic stenosis, and dilated cardiomyopathy, electrocardiogram (ECG) and cardiac magnetic resonance imaging (CMR) are frequently the gold standards. However, asymptomatic people do not undergo these additional instruments; rather, patients who are suspected of having related symptoms do. Early diagnosis of CVDs is made more difficult by the additional techniques' limited efficacy and unsuitability as screening tools for the general public due to their high cost and technical skill requirements. Because of this, many patients often wait until a late stage for a diagnosis, with worse outcomes seen in more advanced illnesses (Wang & Khalil, 2018).

ECG is an often-used supplementary test that is generally straightforward to use, inexpensive, and accessible, even in resource-poor environments. For a long time, ECG has been a highly effective diagnostic tool for heart conditions. However, how a clinician interprets the ECG depends on their level of training and experience. Moreover, one of the main obstacles to effectively exploiting the benefits of the raw ECG waveform is the tens of thousands of data points that make it difficult for clinicians to understand. But thanks to its strong processing power, aptitude for graphic analysis, and learning ability, AI can also extract valuable and subtle information from ECG waveforms that humans cannot see, such as the relationship between specific CVDs and ECG features (World Health Organization, 2011).

Many valvular heart disorders are characterized by extended periods of asymptomatic heart disease. But if symptoms show up, the risk of dying rises sharply. Good outcomes are frequently achieved with follow-up for asymptomatic patients and valve replacement for symptomatic patients. However, locating these asymptomatic people remains difficult. Although echocardiography is not appropriate for screening, it is the gold standard for verifying valvular heart disease diagnoses. The potential use of AI-enhanced Electrocardiograms (AI-ECG) as a screening tool for asymptomatic individuals has therefore been the subject of much discussion (Yan *et al.*, 2019).

Atrial fibrillation (AF) is often asymptomatic and undetectable, especially in paroxysmal AF. Patients with atrial fibrillation (AF) may appear to have a normal sinus rhythm on an ECG, which can result in underdiagnoses. However, changes in the heart's structure occur with the onset of AF. A well-trained neural network could potentially spot subtle differences in normal sinus-rhythm ECGs to predict AF. In a study, a CNN was used to identify patients with AF during a normal sinus rhythm using a 10-second, 12-lead ECG. The model was trained using approximately 500,000 ECGs and achieved an overall accuracy of 79.4% and an AUC of 0.87 for detecting AF from sinus-rhythm ECGs when tested. AI-based prognostic models have seen extensive development in cardiovascular medicine. Advances in applying artificial intelligence to standard 12-lead electrocardiograms have made it possible to forecast the long-term prognosis for patients with cardiovascular disease. building and assessing a DNN model using ECG voltage-time traces to predict death from all causes within a year (Akinyele *et al.*, 2020).

Remote Monzitoring & Management of Patients

A new class of compact, reliable, and efficient computer devices known as smart wearables—also called wearable

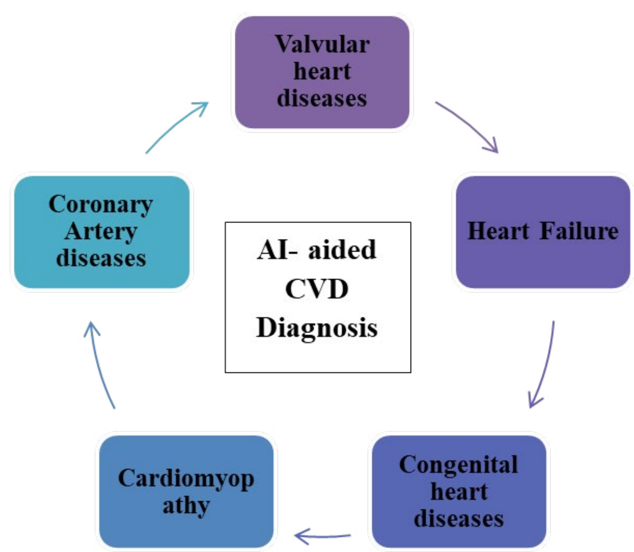

Figure 02: AI–aided CVD Diagnosis

gadgets or smart wearable technology—has been made possible by the quick advancement of electronics, especially microprocessors and information and communication technologies. Since they enable data access anywhere, at any time, these devices are hailed as the next big thing in ubiquitous technology, following smartphones (as shown in fig. 2). The field of smart wearables has grown quickly in the last several years, and a wide range of industries can now benefit from its technology (Attia *et al.*, 2019).

Smart wearables have become more and more popular as health solutions over the last ten years. Their popularity and widespread use can be attributed, among other things, to improvements in performance, size, style, and longevity. Smart wearables such as wristbands, patches, headbands, eyeglasses, and necklaces are used to identify, monitor, and treat cardiovascular disease. Wearables for CVD have numerous ramifications. For instance, they offer long-term, continuous collection of physiological or functional data, improving patient outcomes and accuracy of diagnosis. They also make it possible to gather data in places other than clinics or hospitals, which increases the ability of healthcare providers to offer longer-term treatment to a greater number of patients. Additionally, smart wearables' continuous monitoring capabilities provide a more advanced understanding of each patient's physiological state and current activities, which makes it possible to provide more individualized therapy and healthcare. Additionally, the devices became more aesthetically beautiful and less bulky, which lessened their intrusiveness and increased their acceptability as everyday wearables. Through pairing, smart wearables, like smartphones, can profit from the ubiquitous use of other gadgets (Lee *et al.*, 2022).

Smart Wearables

More than a thousand studies on smart wearables have been conducted in the last few decades. Smart wearables, however, are too diverse to be put into one group. The power, processing, and memory capacities of the computational devices employed in wearable electronics to measure complimentary signals and significant biosignals are constrained. Thus, the creation of thorough end-to-end algorithms is typically the first step in applying AI algorithms for wearable or proximity-portable smart devices. In order to reduce the model size and achieve resource economy, model compression techniques must be applied to the large-scale DL algorithms. Under these circumstances, wearables are limited to offline inference. Models for constrained device implementation are typically compressed via low-rank approximation, pruning, quantization, clustering, and knowledge distillation (Liu *et al.*, 2021).

Remote Patient management

Remote monitoring, or RM, is a crucial part of patient follow-up for patients with cardiac implanted electronic devices (CIEDs). RM requires the cooperation of multiple key components. First and foremost, the patient is at the center of RM, and receiving the associated clinical advantages depends on the patient's compliance with RM. Serving the administrative, non-clinical, and clinical parts of the interdisciplinary team that works with RM is the second location, which is the remote device clinic (Mabo *et al.*, 2012).

A remote telemetry tool that can be used to collect data for several individual patients is the home monitor. Additionally, it can be strategically positioned near the patient and enrolled at a particular site (individual-based RM). The personnel of the remote device clinic can obtain this data thanks to the RM platform. An actionable event is any clinical or device-related incidence that RM finds and for which a quick fix could improve a patient's outcome. Therefore, in addition to individuals with ICDs, patients with pacemakers or implanted loop recorders (ILR) are also impacted. Observational data showed that just 6% of scheduled invoice follow-up visits resulted in changes to patient care or device reprogramming. Moreover, patients with continuous RM were able to reduce the time interval between event identification and medical action to as little as one day (Modarai, 2019).

RM has three main advantages in terms of event detection. Primarily, RM enables the early detection of device and lead faults, such as battery depletion or lead failure. When there are alerts or recalls, this is quite useful for CIEDs. The continuous monitoring greatly reduced the number of unnecessary shocks and symptomatic pacing inhibition in patients with lead failure. The effect of remote monitoring may be most noticeable soon after implantation. Data from the TRUST study showed quicker identification of actionable events requiring device reprogramming or lead adjustment, without increasing the occurrence of non-actionable events (Moglia *et al.*, 2021).

Surgical Planning & Interventions

The training of surgeons may change as a result of the application of AI in surgical education. Since task-based learning and simulation were introduced, surgical training has experienced substantial modifications. AI is a promising addition to this route. Even though AI has a lot of promise, there is a dearth of clinical applications, including its incorporation into official medical curricula (Park *et al.*, 2016).

The training of surgeons may change as a result of the application of AI in surgical education. Since task-based learning and simulation were introduced, surgical training has experienced substantial modifications. AI is a promising addition to this route. Even though AI has a lot of promise, there is a dearth of clinical applications, including its incorporation into official medical curricula. Artificial intelligence (AI) is particularly helpful in simulating surgical procedures, which enables trainees to hone their skills in a safe setting and get a deeper comprehension of the intricate process of surgery (Pucchio *et al.*, 2022). Artificial intelligence (AI) in surgical education has the potential to improve training effectiveness and quality, which will lead to better clinical outcomes. The use of AI in surgical training may grow in popularity as both the field of surgery and technology continue to progress. Since AI's potential and skills keep growing, this integration is probably going to happen in ways that are hard to imagine or predict right now. Artificial intelligence (AI) in surgical education has great promise for transforming the surgical education process and enhancing the overall standard of surgical treatment.

Learning Surgical Competence

Surgical competency includes a broad spectrum of skills. It is conventional wisdom that competency comprises the elements of attitudes, skills, and knowledge. Artificial Intelligence can significantly contribute to the advancement of surgical skills and other aspects of surgical competency. AI is well-suited for simulation-based training, which can expedite the learning curve for surgical procedures. In surgical education, simulation-based training has become essential due to its ability to enhance student confidence and performance. AI, utilizing virtual reality and other simulation technologies, can offer surgical residents and trainees a realistic and secure environment to practice and improve their technical skills (Puliatti *et al.*, 2022). With the aid of simulation-based training, learners can hone their skills and build their confidence in performing treatments without having to worry about putting actual patients in danger.

Surgical Diagnostics and Decision-Making

Diagnostics and decision-making change along with healthcare, putting surgeons-in-training in novel situations. Artificial Intelligence has the potential to greatly increase surgical diagnosis accuracy and efficiency. In the field of artificial intelligence, machine learning is used to extract complicated correlations from independent and dependent variables. Large volumes of data from diverse sources, including patient histories, lab test results, and medical photographs, can be analyzed by machine learning algorithms to find trends and forecast the most likely diagnosis (Sana *et al.*, 2020).

Large datasets can be used to train machine learning algorithms to identify patterns and trends, assisting clinicians in reaching more trustworthy and accurate diagnosis conclusions. It has been noted that certain algorithms, particularly in radiology, yield findings that are comparable to those of doctors.

Learning Minimally Invasive Surgery

Artificial intelligence has great promise for augmenting the safety and efficacy of robotic and minimally invasive surgical procedures. Artificial intelligence (AI) can assist in developing advanced navigation and guidance systems, improving the precision and accuracy of surgical procedures. AI-powered image analysis technologies can be used to identify and monitor internal body structures and surgical instruments, providing real-time guidance to the surgeon during the procedure (Varma *et al.*, 2016). Additionally, these technologies can assist the surgeon in taking timely and appropriate action by aiding in the identification of unforeseen intraoperative occurrences or issues. The development of machine learning algorithms that can analyze surgical data from prior procedures and identify patterns and trends may also profit from AI. This will make it possible to use more tailored and scientifically validated surgical planning and execution techniques. Large datasets can be used to train algorithms to find patterns and trends, that improve surgical decision-making accuracy and reliability. Despite the technology's potential for minimally invasive surgery, there is still a dearth of research on the application of AI in robotic surgery (Winkler-Schwartz *et al.*, 2019).

Future Perspectives & its challenges

Healthcare practitioners use several traditional techniques to predict cardiovascular disease. Conventional approaches to predicting cardiovascular disease include clinical risk variables associated with age, gender, medical history, and family history. Furthermore, an electrocardiogram (ECG) can be used to identify congestive heart failure symptoms, while echocardiography can be utilized to visualize how the heart functions. ECG is especially useful for managing the prognosis and course of treatment for individuals with congestive heart failure. Other common problems with the heart and blood vessels, such as coronary artery disease (CAD), can also be diagnosed and assessed using cardiac catheterization.

Additionally, by eliminating noisy features from the datasets, feature selection approaches can lower the dimensionality of the datasets, improving the accuracy of the prediction models. One dimensionality reduction technique that can be used to reduce the number of features while keeping the majority of the variance is principal component analysis (PCA). AI is a fast-expanding discipline that affects every facet of human effort, including business, sports, science, and medicine. It is crucial to maintain perspective and focus on finding applications of AI that can offer novel healthcare approaches, such as medication therapy and cardiovascular medicine.

Utilizing AI for data-centric applications could lead to new developments in cardiovascular medication therapy and the discovery of novel phenotypes of existing ailments. It's crucial to remember that artificial intelligence (AI) only establishes correlations, not causes. These serve only as hypothesis generators for more in-depth clinical research projects. AI also saves therapists a great deal of time by reducing the time it takes to process data and providing real-time information. By prioritizing pertinent data, AI studies of insertable cardiac monitor-detected episodes, for example, are linked to high classification accuracy and lessen the strain of medical professionals.

Conclusion

Currently, CVD continues to be a significant global health issue, particularly in low- and middle-income nations. For the next twenty years, it will remain the primary cause of death. AI, particularly machine learning, has demonstrated significant promise in the management and treatment of this problematic illness. Furthermore, since artificial intelligence was first created to imitate human thought processes rather than to innovate, we firmly believe that in the future, AI will support clinicians rather than work against them. As a result, the physician needs to be aware of the definition of artificial intelligence and its practical applications. The more doctors learn about the condition; the more powerful AI will be in the coming years. It is imperative for clinicians to always be learning to better serve patients, and they should also avoid relying too heavily on AI and computers. Physicians have a wonderful opportunity and a duty to actively follow the continual advancements of AI techniques and use them as needed to discover appropriate supporting tools for their clinical operations. Customized care is becoming more accessible in the field of cardiovascular medicine because to the introduction of artificial intelligence. The practice of cardiology is going to change, particularly in the area of cardiac imaging, thus doctors must adapt. Healthcare is becoming a pervasive activity as a result of the new relationships that mHealth and telemedicine are fostering between patients and doctors.

References

1. Abouelmehdi, K., Beni-Hessane, A., & Khaloufi, H. (2018). Big healthcare data: preserving security and privacy. *Journal of Big Data, 5*(1), 1. https://doi.org/10.1186/s40537-018-0145-0
2. Attia, Z. I., Harmon, D. M., Behr, E. R., & Friedman, P. A. (2021). Application of artificial intelligence to the electrocardiogram. *European Heart Journal, 42*(46), 4717–4730. https://doi.org/10.1093/eurheartj/ehab520
3. Cheatham, T. E., & Young, M. A. (2000). Molecular dynamics simulation of nucleic acids: Successes, limitations, and promise. *Biopolymers, 56*(4), 232–256. https://doi.org/10.1002/1097-0282(2000)56:4<232::AID-BIP100>3.0.CO;2-K
4. Cheung, A. K., Sarnak, M. J., Yan, G., Dwyer, J. T., Heyka, R. J., Rocco, M. V., Teehan, B. P., & Levey, A. S. (2000). Atherosclerotic cardiovascular disease risks in chronic hemodialysis patients. *Kidney International, 58*(1), 353–362. https://doi.org/10.1046/j.1523-1755.2000.00173.x
5. Cho, H., Keenan, G., Madandola, O. O., Dos Santos, F. C., Macieira, T. G. R., Bjarnadottir, R. I., *et al.* (2022). Assessing the usability of a clinical decision support system: heuristic evaluation. *JMIR Human Factors, 9*(2), e31758. https://doi.org/10.2196/31758
6. Elias, P., Poterucha, T. J., Rajaram, V., Moller, L. M., Rodriguez, V., Bhave, S., *et al.* (2022). Deep learning electrocardiographic analysis for detection of left-sided valvular heart disease. *Journal of the American College of Cardiology, 80*(6), 613–626. https://doi.org/10.1016/j.jacc.2022.06.020
7. Global Atlas on Cardiovascular Disease Prevention and Control. (2011). Geneva, Switzerland: World Health Organization.
8. Helvaci, M. R., Tonyali, O., & Abyad, A. (2019). The safest value of plasma triglycerides. *World Family Medicine Journal/Middle East Journal of Family Medicine, 17*(1), 22–27.
9. Johnson, K. W., *et al.* (2018). Artificial intelligence in cardiology. *Journal of the American College of Cardiology, 71*(23), 2668–2679. https://doi.org/10.1016/j.jacc.2018.03.521
10. Kilic, A. (2020). Artificial intelligence and machine learning in cardiovascular health care. *The Annals of Thoracic Surgery, 109*(5), 1323–1329. https://doi.org/10.1016/j.athoracsur.2020.02.019
11. Kwon, J. M., Lee, S. Y., Jeon, K. H., Lee, Y., Kim, K. H., Park, J., *et al.* (2020). Deep learning-based algorithm for detecting aortic stenosis using electrocardiography. *Journal of the American Heart Association, 9*(7), e014717. https://doi.org/10.1161/JAHA.119.014717
12. Libby, P., Ridker, P. M., & Hansson, G. K. (2011). Progress and challenges in translating the biology of atherosclerosis. *Nature, 473*(7347), 317–325. https://doi.org/10.1038/nature10146
13. Manzoor, A. (2016). RFID in health care-building smart hospitals for quality healthcare. *International Journal of User-Driven Healthcare, 6*(2), 21–45. https://doi.org/10.4018/IJUDH.2016070103
14. Narula, G. (2019). Smart robotics for smart healthcare. *ARME, 1*(5).
15. Roth, G. A., Johnson, C., Abajobir, A., Abd-Allah, F., Abera, S. F., Abyu, G., *et al.* (2017). Global, regional, and national burden of cardiovascular diseases for 10 causes, 1990 to 2015. *Journal of the American College of Cardiology, 70*(1), 1–25. https://doi.org/10.1016/j.jacc.2017.04.052
16. Savoji, H., Mohammadi, M. H., Rafatian, N., Toroghi, M. K., Wang, E. Y., Zhao, Y., *et al.* (2019). Cardiovascular disease models: A game changing paradigm in drug discovery and screening. *Biomaterials, 198*, 3–26. https://doi.org/10.1016/j.biomaterials.2018.08.042
17. Schneider, G. (2010). Virtual screening: An endless staircase? *Nature Reviews Drug Discovery, 9*(4), 273–276. https://doi.org/10.1038/nrd3139
18. Wang, X., & Khalil, R. A. (2018). Matrix metalloproteinases, vascular remodeling, and vascular disease. *Advances in Pharmacology, 81*, 241–330. https://doi.org/10.1016/bs.apha.2017.08.002
19. World Health Organization. (2011). Burden: mortality, morbidity and risk factors. In A. Alwan (Ed.), *Global Status Report on Noncommunicable Diseases 2010* (pp. 9–31). Geneva: World Health Organization.
20. Yan, Y., Zhang, J. W., Zang, G. Y., & Pu, J. (2019). The primary use of artificial intelligence in cardiovascular diseases: What kind of potential role does artificial intelligence play in future medicine? *Journal of Geriatric Cardiology, 16*(8), 585–591. https://doi.org/10.11909/j.issn.1671-5411.2019.08.007
21. Akinyele, B., Marine, J. E., Love, C., Crawford, T. C., Chrispin, J., & Vlay, S. C., *et al.* (2020). Unregulated online sales of cardiac implantable electronic devices in the United States: A six-month assessment. *Heart Rhythm O2, 14*, 235–238. https://doi.org/10.1016/j.hroo.2020.06.003
22. Attia, Z. I., Noseworthy, P. A., Lopez-Jimenez, F., Asirvatham, S. J., Deshmukh, A. J., & Gersh, B. J., *et al.* (2019). An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: A retrospective analysis of outcome prediction. *Lancet, 394*(10201), 861–867. https://doi.org/10.1016/S0140-6736(19)31721-0
23. Lee, K. S., Park, H. J., Kim, J., Kim, H., Chon, S., Kim, S., Jang, J., Kim, J. K., Jang, S., Gil, Y., *et al.* (2022). Compressed deep learning to classify arrhythmia in an embedded wearable device. *Sensors, 22*(1776). https://doi.org/10.3390/s22051776
24. Liu, P. R., Lu, L., Zhang, J. Y., Huo, T. T., Liu, S. X., & Ye, Z. W. (2021). Application of artificial intelligence in medicine: An overview. *Current Medical Science, 41*, 1105–1115. https://doi.org/10.1007/s11596-021-2428-2
25. Mabo, P., Victor, F., Bazin, P., Ahres, S., Babuty, D., & Da Costa, A., *et al.* (2012). A randomized trial of long-term remote monitoring of pacemaker recipients (the COMPAS trial). *European Heart Journal, 33*(9), 1105–1111. https://doi.org/10.1093/eurheartj/ehr419
26. Modarai, B. (2019). Progressive guidance on the modern management of abdominal aorto-iliac artery aneurysms. *European*

Journal of Vascular and Endovascular Surgery, 57, 4–5. https://doi.org/10.1016/j.ejvs.2018.10.028
27. Moglia, A., Georgiou, K., Georgiou, E., Satava, R. M., & Cuschieri, A. (2021). A systematic review on artificial intelligence in robot-assisted surgery. *International Journal of Surgery, 95*, 106151. https://doi.org/10.1016/j.ijsu.2021.106151
28. Park, E., Kim, K. J., & Kwon, S. J. (2016). Understanding the emergence of wearable devices as next-generation tools for health communication. *Information Technology & People, 29*, 717–732. https://doi.org/10.1108/ITP-04-2015-0092
29. Pucchio, A., Rathagirishnan, R., Caton, N., Gariscsak, P. J., Del Papa, J., Nabhen, J. J., Vov, V., Lee, W., & Moraes, F. Y. (2022). Exploration of exposure to artificial intelligence in undergraduate medical education: A Canadian cross-sectional mixed-methods study. *BMC Medical Education, 22*, 815. https://doi.org/10.1186/s12909-022-03731-3
30. Puliatti, S., Eissa, A., Checcucci, E., Piazza, P., Amato, M., Ferretti, S., Scarcella, S., Rivas, J. G., Taratkin, M., Marenco, J., *et al.* (2022). New imaging technologies for robotic kidney cancer surgery. *Asian Journal of Urology, 9*, 253–262. https://doi.org/10.1016/j.ajur.2022.04.003
31. Sana, F., Isselbacher, E. M., Singh, J. P., Heist, E. K., Pathik, B., & Armoundas, A. A. (2020). Wearable devices for ambulatory cardiac monitoring: JACC state-of-the-art review. *Journal of the American College of Cardiology, 75*, 1582–1592. https://doi.org/10.1016/j.jacc.2020.01.070
32. Varma, N., Epstein, A. E., Schweikert, R., Michalski, J., Love, C. J., & Investigators, T. (2016). Role of automatic wireless remote monitoring immediately following ICD implant: The Lumos-T reduces routine office device follow-up study (TRUST) trial. *Journal of Cardiovascular Electrophysiology, 27*(3), 321–326. https://doi.org/10.1111/jce.12911
33. Winkler-Schwartz, A., Bissonnette, V., Mirchi, N., Ponnudurai, N., Yilmaz, R., Ledwos, N., Siyar, S., Azarnoush, H., Karlik, B., & Del Maestro, R. F. (2019). Artificial intelligence in medical education: Best practices using machine learning to assess surgical expertise in virtual reality simulation. *Journal of Surgical Education, 76*, 1681–1690. https://doi.org/10.1016/j.jsurg.2019.05.015

HOW TO CITE THIS ARTICLE: Singh, Y., Bhatt, S., Gupta, D., Verma, S., Deep, P. Harnessing Artificial Intelligence & Machine Learning in Treatment of Cardiovascular Disorders: A Review. J. of Drug Disc. and Health Sci. 2025;2(1):29-36. **DOI:** 10.21590/jddhs.02.01.05