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Journal of Clinical Cardiology and Cardiovascular Interventions
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Open Access

Review Article

Advancements in AI Heart Model Technology: A Comprehensive Review

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Received date: September 13, 2024; **Accepted date:** December 04, 2024; **Published date:** December 19, 2024

Citation: Kiran Dudha ,(2024), Advances in Consultation-Liaison Psychiatry: Bridging Mental and Physical Health Care, *J Clinical Cardiology and Cardiovascular Interventions*,7(14); **DOI:** 10.31579/2641-0419/414

Abstract

Artificial Intelligence (AI) heart models represent a revolutionary approach in cardiovascular medicine, integrating computational models with machine learning to simulate and analyze heart functions, diagnose conditions, and predict patient outcomes. This manuscript provides a comprehensive review of the advancements in AI heart model technology, encompassing data acquisition, model development, and clinical applications. The paper explores various AI algorithms, from traditional machine learning to deep learning, and discusses their roles in enhancing diagnostic accuracy, personalizing treatments, and advancing research. Key challenges and future directions, including ethical considerations and the integration of AI models into clinical practice, are also examined.

Keywords: ai heart models; cardiovascular medicine; machine learning; deep learning, diagnostic tools; computational cardiology;personalized medicine.

Introduction

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, accounting for an estimated 17.9 million deaths annually (World Health Organization, 2021). Traditional diagnostic tools such as echocardiograms, MRI, and CT scans provide crucial insights but are often limited by subjective interpretation, variability in image quality, and the need for extensive training and experience [1]. Artificial Intelligence (AI) heart models have emerged as a transformative solution in cardiovascular medicine, leveraging advanced computational techniques to simulate heart functions, improve diagnostic accuracy, and personalize treatment plans [2].

AI heart models utilize machine learning (ML) algorithms and deep learning (DL) networks trained on vast datasets to predict cardiac events, identify heart abnormalities, and simulate therapeutic outcomes. These models can analyze diverse data types, including medical imaging, genetic information, and electronic health records, to provide a holistic view of a patient's cardiovascular health [3]. This manuscript aims to provide a comprehensive review of AI heart model technology, focusing on its development, current applications, and future potential in clinical practice and research.

2. Data Acquisition for AI Heart Models

Data acquisition is a critical step in developing AI heart models. It involves collecting, pre-processing, and curating data from various sources to ensure quality, diversity, and completeness. The success of an AI heart model heavily depends on the quality and quantity of the input data. The development of accurate and reliable AI heart models hinges on the quality and quantity of the training data used [4]. Collecting comprehensive and diverse datasets is crucial for training these models to recognize complex patterns and make accurate predictions as shown in Table 1. One of the primary sources of data for AI heart models is medical imaging techniques. These include electrocardiograms (ECGs), echocardiograms, cardiac magnetic resonance imaging (CMRI), and computed tomography (CT) scans. ECGs measure electrical activity in the heart, while echocardiograms use sound waves to create images of the heart's structure and function. CMRI and CT scans provide detailed 3D images of the heart and surrounding tissues [5, 6]. Additionally, electronic health records (EHRs) can be a valuable source of data, containing patient demographics, medical history, medications, and clinical outcomes.

Data Acquisition Method	Clinical Implementations	Advantages	Disadvantages
Electrocardiograms (ECGs)[3, 7]	Diagnosing arrhythmias, heart attacks, and other heart conditions	Non-invasive, widely available, and relatively inexpensive	Limited to measuring electrical activity, may not detect structural abnormalities

Echocardiograms[8, 9]	Assessing heart function, detecting structural abnormalities, and evaluating the effects of treatments	Non-invasive, widely available, and can provide detailed images of the heart	Limited by image quality, especially in patients with poor acoustic windows
Cardiac Magnetic Resonance Imaging (CMRI)[10, 11]	Assessing heart function, detecting structural abnormalities, and evaluating the effects of treatments	Highly accurate and provides detailed 3D images	Expensive, time-consuming, and may not be suitable for all patients, especially those with claustrophobia or metal implants
Computed Tomography (CT) Scans[12, 13]	Assessing heart function, detecting coronary artery disease, and evaluating the effects of treatments	Fast and accurate, can provide detailed images of the heart and surrounding tissues	Involves ionizing radiation, which may have long-term health risks
Electronic Health Records (EHRs)[14]	Providing patient demographics, medical history, medications, and clinical outcomes	Comprehensive and can be easily integrated with AI models	May contain incomplete or inaccurate data, and privacy concerns may limit data sharing

Table 1. Different Data Acquisition for AI Heart Models

2.1 Medical Imaging Data

Medical imaging, including echocardiography, magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET), forms the backbone of data for AI heart models. These modalities provide detailed information about heart anatomy, function, and pathology. AI models utilize imaging data to detect structural abnormalities, assess ventricular function, and predict the progression of heart diseases. For example, AI-driven echocardiographic analysis has been shown to enhance the accuracy of left ventricular ejection fraction (LVEF) measurements, a key indicator of heart health [15, 16].

2.2 Electronic Health Records (EHRs)

Electronic Health Records (EHRs) offer a rich source of patient data, including demographics, clinical history, laboratory results, medications, and outcomes. Integrating EHR data with AI heart models allows for the development of personalized models that consider a patient's unique characteristics. Natural Language Processing (NLP) techniques are often employed to extract relevant information from unstructured clinical notes, enhancing the model's predictive capabilities [14, 17].

2.3 Genomic Data

Genomic data, including whole-genome sequencing and single nucleotide polymorphisms (SNPs), provide valuable insights into the genetic predisposition of individuals to various cardiovascular conditions. AI models incorporating genomic data can predict the risk of hereditary heart diseases, such as hypertrophic cardiomyopathy or arrhythmogenic right ventricular cardiomyopathy. Machine learning algorithms can identify patterns in genetic data that correlate with clinical outcomes, providing a foundation for precision medicine [18].

2.4 Wearable and Remote Monitoring Data

Wearable devices and remote monitoring tools, such as smartwatches, fitness trackers, and implantable devices, continuously collect data on heart rate, rhythm, activity levels, and other physiological parameters. AI heart models can utilize this real-time data to monitor patients, detect early signs of heart failure, arrhythmias, and other conditions, and provide timely alerts to healthcare providers. These data are crucial for developing AI models that support remote patient management and telemedicine [19, 20].

3. AI Techniques in Heart Model Development

AI techniques have revolutionized the field of heart model development, offering innovative approaches for analyzing complex medical data and making accurate predictions as depicted in Table 2. Logistic regression, a simple yet powerful technique, is commonly used for risk stratification due to its interpretability. It utilizes linear models to predict binary outcomes, such as the presence or absence of heart disease. Support vector machines (SVMs), on the other hand, are effective for classification tasks involving high-dimensional data, such as detecting arrhythmias. SVMs create a hyperplane to separate data points into different classes, providing a robust and efficient classification method [6, 21].

Random forest, an ensemble learning technique, is well-suited for handling complex, non-linear data. It constructs multiple decision trees and combines their predictions to improve accuracy and reduce overfitting. K-nearest neighbors (K-NN) is another popular technique that leverages similarity measures to classify new data points based on their proximity to existing labeled examples. While K-NN is effective for pattern recognition, it can be sensitive to noise and may struggle with high-dimensional data. Deep learning techniques, such as convolutional neural networks (CNNs), have shown remarkable success in analyzing medical images. CNNs are specifically designed for image data, making them ideal for detecting structural abnormalities in echocardiograms, CT scans, and other imaging modalities [22, 23]. Recurrent neural networks

(RNNs) and long short-term memory (LSTM) networks are well-suited for time-series and sequential data, such as heart rate variability and ECG signals. These techniques can capture temporal dependencies and make predictions based on the history of the data. Developing AI heart models involves multiple techniques, from traditional machine learning methods to advanced deep learning algorithms [24].

AI Technique	Parameters Used	Applications	Examples of Use Cases	Strengths	Limitations
Logistic Regression[25]	Feature coefficients,	Risk prediction, binary classification	Predicting the likelihood of	Simple, interpretable, effective for	Limited to linear relationships, may not

	intercepts, thresholds		myocardial infarction based on risk factors	binary classification	handle complex data well
Support Vector Machines (SVM)[26, 27]	Kernel type, regularization parameter (C), gamma, margin	Classification of cardiac events, arrhythmia detection	Classifying atrial fibrillation from ECG data	Effective for high-dimensional data, robust to overfitting	Requires careful tuning, less interpretable
Random Forest[28, 29]	Number of trees, depth of trees, split criteria	Feature selection, risk stratification, outcome prediction	Predicting heart failure outcomes using EHR data	Handles non-linearity, reduces overfitting, interpretable feature importance	Computationally intensive, less interpretable at a detailed level
K-Nearest Neighbors (K-NN)[30, 31]	Number of neighbors (K), distance metric	Pattern recognition, classification	Detecting abnormalities in heart sound data	Simple, intuitive, non-parametric	Sensitive to noise and irrelevant features
Convolutional Neural Networks (CNN)[32, 33]	Number of layers, filter size, stride, pooling, learning rate	Image analysis, segmentation, classification	Automated detection of coronary artery disease in CT angiography images	High accuracy in image recognition tasks, handles spatial hierarchies	Data-hungry, requires substantial computational resources
Recurrent Neural Networks (RNN)[34]	Number of hidden units, learning rate, sequence length	Sequential data analysis, time-series prediction	Predicting arrhythmias from continuous ECG monitoring data	Effective for sequential data, captures temporal dependencies	Prone to vanishing gradient problems, computationally expensive
Long Short-Term Memory (LSTM)[35]	Number of layers, learning rate, sequence length, dropout rate	Time-series prediction, anomaly detection	Detecting heart failure decompensation using remote monitoring data	Addresses vanishing gradient, effective for long sequences	Requires large datasets, complex architecture
Hybrid Models[34]	Combination of multiple parameters (CNN + LSTM, etc.)	Multi-modal data integration, comprehensive patient profiling	Combining imaging and EHR data to predict cardiac events	Combines strengths of multiple models, versatile	Complexity in model design, requires expertise
Reinforcement Learning (RL)[36, 37]	Reward function, learning rate, discount factor	Optimizing treatment strategies, personalized care	Dynamic adjustment of medication in heart failure management	Learns optimal strategies, adapts over time	Requires large data for training, interpretability issues
Autoencoders[38]	Encoder/decoder structure, bottleneck size, learning rate	Feature extraction, anomaly detection	Identifying abnormal ECG patterns by reconstructing normal signals	Reduces dimensionality, useful for unsupervised learning	May not always converge, complex to train
Graph Neural Networks (GNN)[39, 40]	Number of layers, edge features, node features, aggregation function	Modeling relationships, network-based predictions	Predicting cardiac events by analyzing patient networks and disease connections	Captures complex relationships, suitable for non-Euclidean data	Still emerging in medical applications, requires large datasets
Explainable AI Techniques[41, 42]	Attention mechanisms, saliency maps, interpretable models	Enhancing interpretability, transparency in decision-making	Explaining CNN decisions in diagnosing heart failure from echocardiograms	Improves trust in AI models, regulatory compliance	Balancing interpretability with model complexity

Table 2. AI Techniques in Heart Model Development

3.1 Traditional Machine Learning Methods

Traditional machine learning methods, including logistic regression, support vector machines (SVM), random forests, and k-nearest neighbors (k-NN), have been widely used in cardiovascular research. These methods are effective for tasks such as risk stratification, outcome prediction, and classification of cardiac events. For example, SVM has been applied to predict atrial fibrillation from ECG data, achieving high sensitivity and specificity. Traditional machine learning algorithms have been widely applied to heart model development, providing valuable insights and predictive capabilities. Logistic regression is a commonly used technique for binary classification tasks, such as predicting the presence or absence of heart disease. It employs linear models to estimate the probability of an event occurring based on a set of predictor variables [43]. Support vector machines (SVMs) are another effective method for classification, particularly when dealing with high-dimensional data. SVMs construct a hyperplane to separate data points into different classes, maximizing the margin between them. Decision trees and random forests are ensemble learning techniques that create multiple decision trees and combine their predictions to improve accuracy and reduce overfitting. Naive Bayes classifiers are probabilistic models that assume independence between predictor variables, making them computationally efficient but potentially less accurate in real-world scenarios. K-nearest neighbors (K-NN) is a non-parametric algorithm that classifies new data points based on their similarity to existing labeled examples. While K-NN is effective for pattern recognition, it can be sensitive to noise and may struggle with high-dimensional data [44, 45].

3.2 Deep Learning Techniques

Deep learning techniques, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have revolutionized AI heart modeling. CNNs excel in analyzing medical images, enabling automated detection of coronary artery disease, heart failure, and other conditions with remarkable accuracy. RNNs, including their advanced variant long short-term memory (LSTM) networks, are effective for sequential data analysis, such as ECG signals, providing robust tools for detecting arrhythmias. Deep learning, a subset of machine learning, has gained significant attention in recent years due to its ability to learn complex patterns from large datasets. Convolutional neural networks (CNNs) are particularly well-suited for analyzing medical images, such as echocardiograms and CT scans. CNNs extract features from the image data through successive layers of convolution, pooling, and fully connected layers [25, 46]. Recurrent neural networks (RNNs), including long short-term memory (LSTM) networks, are effective for processing sequential data, such as ECG signals and time-series data. RNNs can capture temporal dependencies and make predictions based on the history of the data. Generative adversarial networks (GANs) are another deep learning technique that can be used to generate synthetic heart data, expanding the available training datasets and improving model performance [47].

3.3 Hybrid Models

Hybrid AI models combine multiple machine learning and deep learning techniques to improve predictive accuracy and generalizability. For instance, a hybrid model may use a CNN for image analysis and an LSTM for time-series data, allowing comprehensive analysis of a patient's cardiac health. These models are particularly valuable for tasks that require integration of multiple data types, such as imaging and EHR data. Hybrid models combine multiple AI techniques to leverage their strengths and address their limitations. For example, a hybrid model could combine a deep learning model for feature extraction with a traditional machine learning model for classification. This approach can improve prediction accuracy and interpretability [35, 48]. Another hybrid approach involves integrating deep learning with knowledge graphs to incorporate domain-specific knowledge and enhance model performance. By combining different AI techniques, researchers can develop more robust and accurate heart models [49].

3.4 Reinforcement Learning

Reinforcement learning (RL) has emerged as a promising approach for developing AI heart models that can learn optimal strategies for managing cardiovascular conditions. RL algorithms use a trial-and-error approach to optimize decision-making, such as determining the best therapeutic regimen for a patient based on their unique clinical profile. Early studies have demonstrated the potential of RL in optimizing heart failure management and personalized treatment planning. Reinforcement learning is a type of machine learning that trains agents to make decisions in an environment to maximize rewards. In the context of heart model development, reinforcement learning can be used to optimize treatment strategies or develop personalized treatment plans. Agents learn through trial and error, interacting with the environment and receiving feedback in the form of rewards or penalties. Reinforcement learning can be applied to simulate heart disease progression and evaluate the effectiveness of different treatment options [25, 50].

4. Applications of AI Heart Models in Clinical Practice

AI heart models have a wide range of applications in clinical practice, from diagnosis to treatment planning and monitoring. AI heart models have the potential to revolutionize clinical practice by providing valuable insights and supporting decision-making processes. One of the key applications of AI heart models is in early diagnosis and risk stratification. By analyzing medical data, such as ECGs, echocardiograms, and clinical variables, AI models can identify patients at high risk of heart disease, enabling early intervention and improved outcomes [6]. AI heart models can also be used for personalized treatment planning, tailoring therapeutic strategies to individual patients based on their unique characteristics and risk factors. These models can help optimize treatment decisions, improve patient outcomes, and reduce healthcare costs. Furthermore, AI heart models can assist in remote monitoring and telemedicine, enabling continuous monitoring of patients' heart health and early detection of adverse events. This can be particularly beneficial for patients living in remote areas or with limited access to healthcare facilities [22]. Additionally, AI heart models can be used for drug discovery and development, accelerating the identification of new therapeutic targets and the development of innovative treatments for heart disease. By analyzing large datasets and identifying patterns that may not be apparent to human experts, AI can contribute to the advancement of cardiovascular medicine [2].

4.1 Diagnostic Tools

AI heart models enhance diagnostic accuracy by providing automated analysis of medical images and physiological signals. For example, AI algorithms can identify subtle abnormalities in echocardiograms that might be missed by human observers, leading to earlier detection of conditions like hypertrophic cardiomyopathy or valvular heart diseases. Additionally, AI-based ECG interpretation tools can detect arrhythmias with greater accuracy and speed than conventional methods, reducing diagnostic delays and improving patient outcomes [51].

4.2 Personalized Treatment Planning

AI heart models enable personalized treatment planning by considering a patient's unique clinical characteristics, genetic profile, and real-time monitoring data. Machine learning algorithms can predict individual responses to specific medications, allowing for tailored treatment regimens that maximize efficacy while minimizing adverse effects. For instance, AI models have been developed to predict the response to beta-blockers in heart failure patients, optimizing medication selection and dosage [52, 53].

4.3 Remote Monitoring and Management

The integration of AI heart models with wearable devices and remote monitoring tools facilitates continuous patient monitoring, early detection of adverse events, and timely intervention. AI algorithms can analyze data from smartwatches and implantable devices to detect arrhythmias, heart failure exacerbations, or ischemic events, prompting immediate alerts to healthcare providers. This approach supports proactive management and reduces hospitalizations [5, 54].

4.4 Predictive Analytics

AI heart models excel in predictive analytics, enabling the identification of patients at high risk for cardiovascular events such as heart attacks, strokes, or sudden cardiac death. By analyzing historical data, AI algorithms can identify patterns and risk factors that may not be apparent to clinicians. This information allows for early intervention, potentially preventing adverse events and improving long-term outcomes [55].

5. Current Challenges in AI Heart Model Technology

Despite the significant potential of AI heart models, several challenges must be addressed to ensure their widespread adoption in clinical practice. Despite the significant advancements in AI heart model technology, several challenges remain to be addressed. One of the primary challenges is the availability of high-quality and diverse datasets. Many existing datasets may be limited in size, suffer from biases, or lack comprehensive patient information. This can hinder the development of accurate and robust AI models. Another challenge is the complexity of the human heart and the variability of cardiovascular disease [56]. AI models must be able to capture the intricate interactions between different factors, including genetics, lifestyle, and environmental influences. Additionally, ensuring the interpretability and explainability of AI models is essential for clinical adoption. Black-box models, which provide predictions without revealing the underlying reasoning, can be difficult to trust and may not be accepted by healthcare providers [57]. Moreover, addressing ethical concerns related to data privacy, bias, and fairness is crucial for the responsible development and deployment of AI heart models. Ensuring that these models are equitable and do not perpetuate existing disparities is essential for their widespread adoption in clinical practice [58].

5.1 Data Quality and Diversity

One of the primary challenges in developing robust AI heart models is the quality and diversity of input data. Most AI models rely on large datasets, which may not always represent diverse populations. Data bias, incomplete records, and poor-quality images can significantly impact model performance. Standardizing data collection and ensuring diverse representation are critical for developing AI models that are generalizable and equitable [59].

5.2 Interpretability and Transparency

AI heart models, particularly deep learning algorithms, are often considered "black boxes" due to their complex and opaque nature. Clinicians and regulatory bodies require interpretability and transparency to trust AI models in decision-making. Developing explainable AI techniques that provide insight into model decision processes is crucial for gaining acceptance and ensuring patient safety [60].

5.3 Integration into Clinical Workflow

Integrating AI heart models into clinical workflows presents logistical and technical challenges. Healthcare systems must ensure that these models are compatible with existing electronic health records and imaging systems and that they do not disrupt routine clinical operations. Adequate training and support for healthcare providers are also essential for the successful adoption of AI tools [61].

5.4 Regulatory and Ethical Considerations

The use of AI heart models raises several regulatory and ethical considerations, including data privacy, informed consent, and the potential for bias in decision-making. Regulatory bodies like the U.S. FDA and European Medicines Agency (EMA) have begun to establish guidelines for AI in healthcare, but these are still evolving. Ethical considerations, such as ensuring transparency, fairness, and accountability, must be addressed to build trust in AI technologies [62].

6. Future Directions in AI Heart Model Technology

AI heart model technology is rapidly evolving, with several promising developments on the horizon. The field of AI heart model technology is rapidly evolving, with promising future directions that have the potential to revolutionize cardiovascular medicine. One area of focus is the development of more sophisticated deep learning architectures that can capture the complex patterns and interactions within the human heart. Incorporating domain-specific knowledge into AI models can also enhance their performance and interpretability. Furthermore, the integration of AI with wearable devices and other medical technologies can enable continuous monitoring of heart health and early detection of abnormalities. Advances in data science and machine learning techniques will also play a crucial role in developing more accurate and reliable AI heart models. Additionally, addressing ethical concerns and ensuring the responsible development and deployment of AI heart models will be essential for their widespread adoption in clinical practice [63, 64]. By overcoming these challenges and embracing the opportunities presented by AI, researchers can continue to push the boundaries of heart model technology and improve the diagnosis, treatment, and prevention of cardiovascular disease.

6.1 Integration of Multi-Omics Data

Integrating multi-omics data, including genomics, proteomics, and metabolomics, with AI heart models offers the potential for truly personalized medicine. By combining molecular data with clinical and imaging data, AI models can provide deeper insights into disease mechanisms and predict individual responses to therapies more accurately [65].

6.2 Development of Explainable AI Models

Research is increasingly focused on developing explainable AI models that provide clear, interpretable insights into their decision-making processes. Techniques such as attention mechanisms, saliency maps, and decision trees are being explored to make AI models more transparent and understandable to clinicians and patients [42].

6.3 AI in Digital Twin Technology

The concept of a "digital twin" involves creating a virtual replica of a patient's heart using AI and computational modeling. This digital twin can be used to simulate various treatment scenarios, predict outcomes, and optimize therapeutic strategies in real time. Digital twins hold immense potential for personalized medicine, particularly in complex cardiovascular conditions like heart failure or congenital heart disease [66, 67].

6.4 AI-Driven Drug Discovery and Development

AI heart models are poised to play a crucial role in drug discovery and development by identifying potential drug targets, predicting drug efficacy, and simulating clinical trials. AI can accelerate the drug development process, reduce costs, and increase the likelihood of success by providing more accurate predictions of drug behavior in the human body [68, 69].

6.5 Advanced Imaging Techniques

Combining AI with advanced imaging techniques, such as 4D flow MRI or functional CT, offers the potential for more accurate and detailed assessments of cardiac function and structure. AI algorithms can analyze these complex datasets more efficiently than traditional methods, providing new insights into disease mechanisms and improving diagnostic accuracy [70, 71].

7. Conclusion

AI heart model technology represents a transformative advancement in cardiovascular medicine, offering the potential to improve diagnostic accuracy, personalize treatment plans, and enhance patient outcomes. Despite the challenges, ongoing research and development are rapidly expanding the capabilities of AI models, moving towards more comprehensive, explainable, and clinically integrated solutions. Future advancements, including the integration of multi-omics data, digital twin technology, and AI-driven drug discovery, hold immense promise for the continued evolution of this field. Addressing challenges related to data quality, interpretability, and ethical considerations will be key to realizing the full potential of AI heart models in clinical practice.

Declarations

Consent for publication Nil

Authors' contributions

Study conception and design, data collection, analysis and interpretation of results, and manuscript preparation by K.D.

Conflict of interests

The authors declare no conflict of interests.

Acknowledgments

No acknowledgments

Ethical declaration

No animal or human subjects were used during the preparation of this manuscript.

Funding

No

Data availability Statement

Data sharing is not applicable to this review article as no datasets were generated or analyzed during the current study.

References

1. Bansal M. (2020). Cardiovascular disease and COVID-19. Diabetes & Metabolic Syndrome: Clinical Research & Reviews.;14(3):247-250.
2. Wang DD, Qian Z, Vukicevic M, et al. (2021). 3D printing, computational modeling, and artificial intelligence for structural heart disease. Cardiovascular Imaging.;14(1):41-60.
3. Akbilgic O, Butler L, Karabayir I, et al. (2021).ECG-AI: electrocardiographic artificial intelligence model for prediction of heart failure. European Heart Journal-Digital Health.;2(4):626-634.
4. Yasmin F, Shah SMI, Naeem A, et al. (2020).Artificial intelligence in the diagnosis and detection of heart failure: the past, present, and future. Reviews in cardiovascular medicine. 2021;22(4):1095-1113.
5. Choi D-J, Park JJ, Ali T, et al (2020).Artificial intelligence for the diagnosis of heart failure. NPJ digital medicine.;3(1):54.
6. Sermesant M, Delingette H, Cochet H, et al.(2021).Applications of artificial intelligence in cardiovascular imaging. Nature Reviews Cardiology.;18(8):600-609.
7. Kwon J-m, Jo Y-Y, Lee SY, et al. (2022). Artificial intelligence-enhanced smartwatch ECG for heart failure-reduced ejection fraction detection by generating 12-lead ECG. Diagnostics.;12(3):654.
8. Akkus Z, Aly YH, Attia IZ, et al. (2021). Artificial intelligence (AI)-empowered echocardiography interpretation: a state-of-the-art review. Journal of clinical medicine.;10(7):1391.
9. Yoon YE, Kim S, Chang H-J. (2021). Artificial intelligence and echocardiography. Journal of Cardiovascular Imaging.;29(3):193.
10. Cau R, Cherchi V, Micheletti G, et al. (2021). Potential role of artificial intelligence in cardiac magnetic resonance imaging: can it help clinicians in making a diagnosis? Journal of thoracic imaging.;36(3):142-148.
11. Argentiero A, Muscogiuri G, Rabbat MG, et al. (2022). The applications of artificial intelligence in cardiovascular magnetic resonance—a comprehensive review. Journal of Clinical Medicine.;11(10):2866.
12. Yang DH. (2021). Application of artificial intelligence to cardiovascular computed tomography. Korean Journal of Radiology.;22(10):1597.
13. McCollough C, Leng S. (2020). Use of artificial intelligence in computed tomography dose optimisation. Annals of the ICRP.;49(1_suppl):113-125.
14. Wesołowski S, Lemmon G, Hernandez EJ, et al.(2022). An explainable artificial intelligence approach for predicting cardiovascular outcomes using electronic health records. PLOS digital health.;1(1):e0000004.
15. Willemink MJ, Koszek WA, Hardell C, et al.(2020). Preparing medical imaging data for machine learning. Radiology.;295(1):4-15.
16. Diaz O, Kushibar K, Osuala R, et al. (2021).Data preparation for artificial intelligence in medical imaging: A comprehensive guide to open-access platforms and tools. Physica medica.;83:25-37.
17. Samaras A, Bekiaridou A, Papazoglou AS, et al. (2023).Artificial intelligence-based mining of electronic health record data to accelerate the digital transformation of the national cardiovascular ecosystem: design protocol of the CardioMining study. BMJ open.;13(4):e068698.
18. Quazi S.(2022). Artificial intelligence and machine learning in precision and genomic medicine. Medical Oncology.;39(8):120.
19. Huang J-D, Wang J, Ramsey E, et al. (2022). Applying artificial intelligence to wearable sensor data to diagnose and predict cardiovascular disease: a review. Sensors.;22(20):8002.
20. Phatak AA, Wieland F-G, Vempala K, et al. (2021). Artificial intelligence based body sensor network framework—narrative review: proposing an end-to-end framework using wearable sensors, real-time location systems and artificial intelligence/machine learning algorithms for data collection, data mining and knowledge discovery in sports and healthcare. Sports Medicine-Open.;7(1):79.
21. Dampage U, Balasuriya C, Thilakarathna S, et al., (2021).editors. AI-based heart monitoring system. 2021 IEEE 4th International Conference on Computing, Power and Communication Technologies (GUCON);: IEEE.
22. Lopez-Jimenez F, Attia Z, Arruda-Olson AM, et al., (2020).editors. Artificial intelligence in cardiology: present and future. Mayo Clinic Proceedings;: Elsevier.
23. Puiu A, Vizitiu A, Nita C, et al. (2021).Privacy-preserving and explainable AI for cardiovascular imaging. Studies in Informatics and Control.;30(2):21-32.
24. Gadde SS, Kalli VDR. (2020).Artificial Intelligence To Detect Heart Rate Variability. International Journal of Engineering Trends and Applications.;7(3):6-10.
25. Chang V, Bhavani VR, Xu AQ, et al. An artificial intelligence model for heart disease detection using machine learning algorithms. Healthcare Analytics. 2022;2:100016.
26. Faieq AK, Mijwil MM. (2022). Prediction of heart diseases utilising support vector machine and artificial neural network. Indonesian Journal of Electrical Engineering and Computer Science.;26(1):374-380.
27. Aggarwal Y, Das J, Mazumder PM, et al. (2020).Heart rate variability features from nonlinear cardiac dynamics in identification of diabetes using artificial neural network and support vector machine. Biocybernetics and Biomedical Engineering.;40(3):1002-1009.
28. Saikumar K, Rajesh V. A novel implementation heart diagnosis system based on random forest machine learning technique.

International Journal of Pharmaceutical Research (09752366). 2020.
29. Asadi S, Roshan S, Kattan MW. (2021). Random forest swarm optimization-based for heart diseases diagnosis. Journal of biomedical informatics.;115:103690.
30. Anggoro DA, Aziz NC.(2021). Implementation of K-nearest neighbors algorithm for predicting heart disease using python flask. Iraqi Journal of Science.:3196-3219.
31. Yaqoob M, Iqbal F, Zahir S. (2020). Comparing predictive performance of k-nearest neighbors and support vector machine for predicting ischemic heart disease. Research Journal in Advanced Sciences.;1(2):49-60.
32. Arooj S, Rehman Su, Imran A, et al. (2022).A deep convolutional neural network for the early detection of heart disease. Biomedicines.;10(11):2796.
33. Mehmood A, Iqbal M, Mehmood Z, et al. (2021).Prediction of heart disease using deep convolutional neural networks. Arabian Journal for Science and Engineering.;46(4):3409-3422.
34. Krishnan S, Magalingam P, Ibrahim R. (2021).Hybrid deep learning model using recurrent neural network and gated recurrent unit for heart disease prediction. International Journal of Electrical & Computer Engineering (2088-8708);11(6).
35. Bhavekar GS, Goswami AD. (2022).A hybrid model for heart disease prediction using recurrent neural network and long short term memory. International Journal of Information Technology.;14(4):1781-1789.
36. Mohammed MA, Ramakrishnan R, Mohammed MA, et al., (2023).editors. A Novel Predictive Analysis to Identify the Weather Impacts for Congenital Heart Disease Using Reinforcement Learning. 2023 International Conference on Network, Multimedia and Information Technology (NMITCON);: IEEE.
37. Guo H, Li J, Liu H, et al. (2022). Learning dynamic treatment strategies for coronary heart diseases by artificial intelligence: real-world data-driven study. BMC Medical Informatics and Decision Making.;22(1):39.
38. Kaushal B, Raveendran S, Patil MD, et al. (2023).Deep autoencoder neural networks for heart sound classification. Artificial intelligence in medical virology: Springer;. p. 165-189.
39. Sharma A, Singh PK, Nikashina P, et al. (2023).AI and GNN model for predictive analytics on patient data and its usefulness in digital healthcare technologies. IoT, Big Data and AI for Improving Quality of Everyday Life: Present and Future Challenges: IOT, Data Science and Artificial Intelligence Technologies: Springer; p. 331-345.
40. Lu H, Uddin S. (2021).A weighted patient network-based framework for predicting chronic diseases using graph neural networks. Scientific reports.;11(1):22607.
41. Dave D, Naik H, Singhal S, et al. (2020).Explainable ai meets healthcare: A study on heart disease dataset. arXiv preprint arXiv:201103195.
42. Dwivedi R, Dave D, Naik H, et al. Explainable AI (XAI): Core ideas, techniques, and solutions. ACM Computing Surveys. 2023;55(9):1-33.
43. Birim S, Kazancoglu I, Mangla SK, et al. (2024).The derived demand for advertising expenses and implications on sustainability: a comparative study using deep learning and traditional machine learning methods. Annals of Operations Research.;339(1):131-161.
44. Wang P, Fan E, Wang P. (2021). Comparative analysis of image classification algorithms based on traditional machine learning and deep learning. Pattern recognition letters.;141:61-67.
45. Avci O, Abdeljaber O, Kiranyaz S, et al. (2021).A review of vibration-based damage detection in civil structures: From traditional methods to Machine Learning and Deep Learning applications. Mechanical systems and signal processing.;147:107077.
46. Swathy M, Saruladha K. (2022).A comparative study of classification and prediction of Cardio-Vascular Diseases (CVD) using Machine Learning and Deep Learning techniques. ICT express.;8(1):109-116.
47. Abubaker MB, Babayiğit B. (2022).Detection of cardiovascular diseases in ECG images using machine learning and deep learning methods. IEEE transactions on artificial intelligence. 4(2):373-382.
48. Suresh T, Assegie TA, Rajkumar S, et al.(2022). A hybrid approach to medical decision-making: diagnosis of heart disease with machine-learning model. Int J Elec Comp Eng;12(2):1831-1838.
49. Shrivastava PK, Sharma M, Kumar A. (2023).HCBiLSTM: A hybrid model for predicting heart disease using CNN and BiLSTM algorithms. Measurement: Sensors;25:100657.
50. Guo A, Pasque M, Loh F, et al. (2020).Heart failure diagnosis, readmission, and mortality prediction using machine learning and artificial intelligence models. Current Epidemiology Reports. 2020;7:212-219.
51. Alowais SA, Alghamdi SS, Alsuhebany N, et al.(2023). Revolutionizing healthcare: the role of artificial intelligence in clinical practice. BMC medical education.;23(1):689.
52. Attia ZI, Harmon DM, Behr ER, et al.(2021). Application of artificial intelligence to the electrocardiogram. European heart journal.;42(46):4717-4730.
53. Busnatu Ș, Niculescu A-G, Bolocan A, et al.(2022). Clinical applications of artificial intelligence—an updated overview. Journal of clinical medicine.;11(8):2265.
54. Siontis KC, Noseworthy PA, Attia ZI, et al.(2021). Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. Nature Reviews Cardiology.;18(7):465-478.
55. Karatzia L, Aung N, Aksentijevic D. (2022). Artificial intelligence in cardiology: Hope for the future and power for the present. Frontiers in Cardiovascular Medicine.;9:945726.
56. Nazir MB, Hussain I. (2024).Revolutionizing Cardiac Care: AI and Deep Learning in Heart Health. International Journal of Advanced Engineering Technologies and Innovations.;1(4):189-208.
57. Singh RP, Hom GL, Abramoff MD, et al. (2020).Current challenges and barriers to real-world artificial intelligence adoption for the healthcare system, provider, and the patient. Translational Vision Science & Technology.;9(2):45-45.
58. Nasr M, Islam MM, Shehata S, et al. (2021).Smart healthcare in the age of AI: recent advances, challenges, and future prospects. IEEE Access.;9:145248-145270.
59. Kakhi K, Alizadehsani R, Kabir HD, et al.(2022). The internet of medical things and artificial intelligence: trends, challenges, and opportunities. Biocybernetics and Biomedical Engineering.;42(3):749-771.
60. Feeny AK, Chung MK, Madabhushi A, et al.(2020). Artificial intelligence and machine learning in arrhythmias and cardiac electrophysiology. Circulation: Arrhythmia and Electrophysiology. 13(8):e007952.
61. Park C-W, Seo SW, Kang N, et al.(2020). Artificial intelligence in health care: current applications and issues. Journal of Korean medical science.;35(42).
62. Lewin S, Chetty R, Ihdayhid AR, et al. (2024).Ethical challenges and opportunities in applying artificial intelligence to cardiovascular medicine. Canadian Journal of Cardiology.

63. Arefin S. AI (2024). Revolutionizing Healthcare: Innovations, Challenges, and Ethical Considerations. MZ Journal of Artificial Intelligence.;1(2):1− 17-1− 17.
64. Nakamura T, Sasano T. (2022).Artificial intelligence and cardiology: Current status and perspective. Journal of Cardiology.;79(3):326-333.
65. Tong L, Shi W, Isgut M, et al.(2023). Integrating multi-omics data with EHR for precision medicine using advanced artificial intelligence. IEEE Reviews in Biomedical Engineering..
66. Coorey G, Figtree GA, Fletcher DF, et al. (2022).The health digital twin to tackle cardiovascular disease—a review of an emerging interdisciplinary field. NPJ digital medicine.;5(1):126.
67. Arora P, Behera M, Saraf SA, et al. (2024).Leveraging Artificial Intelligence for Synergies in Drug Discovery: From Computers to Clinics. Current Pharmaceutical Design.;30(28):2187-2205.
68. Narayanan RR, Durga N, Nagalakshmi S. (2022).Impact of artificial intelligence (AI) on drug discovery and product development. Indian Journal of Pharmaceutical Education and Research.;56(3):S387-S397.
69. Boniolo F, Dorigatti E, Ohnmacht AJ, et al. (2021).Artificial intelligence in early drug discovery enabling precision medicine. Expert Opinion on Drug Discovery.;16(9):991-1007.
70. Malandraki-Miller S, Riley PR.(2021). Use of artificial intelligence to enhance phenotypic drug discovery. Drug Discovery Today.;26(4):887-901.
71. Mak K-K, Balijepalli MK, Pichika MR. (2022).Success stories of AI in drug discovery-where do things stand? Expert opinion on drug discovery.;17(1):79-92.

DOI: 10.31579/2641-0419/414