Journal port Science Research
https://jpsr.uruk.edu.iq/index.php/jport
Volume 9, issue 2. 2026

Electrocardiography Techniques for the Prediction and Detection of Coronary Artery Disease: Intelligent Diagnostic Support Systems

Fatima Q. Al-Rawi [a], Farah Qahtan [b], Moatasim Amer Mohammed [a]

[a] *Department of Intelligent Medical Systems, College of Biomedical Informatics, University of Information Technology and Communications, Baghdad, Iraq.*

[b] *Department of Bioinformatics, College of Biomedical Informatics, University of Information Technology and Communications, Baghdad, Iraq.*

ARTICLE INFO

Keywords:

ECG, Coronary Artery Disease, AI

ABSTRACT

The high world rate of mortality around is attributable to Coronary Artery Disease (CAD). Therefore, in order to prevent extreme outcomes (including coronary heart attacks and sudden death, early detection is essential. A diagnostic (non-invasive) tool commonly used to identify early symptoms of CAD is Electrocardiography (ECG). However, the interpreter's knowledge may overlook diffuse patterns, thus affecting the accuracy. Artificial Intelligence (AI) is a promising solution that has emerged recently. That is because it can utilize advanced algorithms to analyze large ECG datasets and identify previously hidden indicators of early-stage disease. This research demonstrates the significance of ECG in CAD diagnosis and investigates how AI can enhance diagnostic accuracy to improve preventive measures for cardiac disease.

1. INTRODUCTION

In 1996, cardiovascular disease (CVD) became the primary contributor to high death rates around the world, by 29%(Duncker et al., 2021). CAD is the predominant cause of death and disease internationally, responsible for 16% percent of all fatalities. According to the World Health Organization (2020), CAD is responsible for approximately nine million deaths annually. According to the International Burden of Disease Research Study (2021), it affects 126 million individuals all over the world (around 17.2 per cent of the worldwide population). The recent years in the Middle East/North African region have witnessed a decrease in Years Lived with Disability (YLD) and age-standardized mortality by 9% and 35% respectively. Nevertheless, the highest global rates of cardiovascular diseases come from this region(Hosseini et al., 2021),(Di Lenarda et al., 2024).

Significant progress has been made in understanding the pathophysiology of coronary artery disease (CAD) over the last decade. CAD is among the CVD entities, which also consist of high blood pressure, stroke, muscular, valvular and congenital heart ailments. CAD is fundamentally associated with the development of atherosclerotic plaques within the artery walls, a phenomenon that remains inadequately understood despite various pathophysiological factors. The popular technique of coronary atherosclerosis involves several stages: endothelial dysfunction and subendothelial buildup of low-density lipoprotein (LDL); oxidation of LDL; migration of monocytes, which migrate to the subendothelial region and their transformation into macrophages; formation of foam cells; proliferation of smooth muscle cells; and ultimately, apoptosis of foam cells, resulting in the development of necrotic cores. This technique exemplifies an intricate and heterogeneous method that requires several years to yield macroscopic evidence in the form of plaque. Several systemic hazard elements, including hyperlipidemia, excessive blood pressure, hereditary factors, and vascular functions that define wall shear pressure and other blood flow hemodynamic factors, all contribute to the multifaceted approach to plaque formation(Sayols-Baixeras, Lluís-Ganella, Lucas, & Elosua, 2014),(Achim et al., 2023). Although effective management of cardiovascular disease lowers mortality, a strong focus is put on early recognition, prevention, and, where necessary, rapid treatment of vascular disorders. In cardiology, Cardiograms are the most commonly used type of test and are generally the most widely utilized clinical device for diagnosing cardiac illnesses, due to their widespread availability, low cost, painlessness, and

E-mail address:
fatima.kasim-bic@uoitc.edu.iq [a]
Farah.qahtan-bic@uoitc.edu.iq - [b]
moatasim.amer@uoitc.edu.iq [c]

Corresponding* : *Fatima Q. Al-Rawi*

Received 3th February 2026، Accepted 22th March 2026

10.36371/port.2026.2.10

ease of use. An ECG is a recording of the heart's electrical activity detected on the body's surface. A high level of skill and expertise in assessment is required for interpreting an ECG (With the assistance of a cardiologist). A professional's classical evaluation enables the diagnosis of specific scientific problems through a macroscopic evaluation of character segment changes, such as atrial traumatic inflammation (AF), ventricular hypertrophy, or acute coronary syndromes (ACS) with ST-segment elevations or depressions(Di Costanzo, Spaccarotella, Esposito, & Indolfi, 2024). The introduction of sophisticated computational techniques and Artificial Intelligence (AI) has led to a significant evolution in healthcare diagnostics. Over the last decade, improved deep learning (DL) and machine learning (ML) modalities that utilize ECG data and unique, significant signal evaluations to assess a patient's cardiovascular status and aid doctors in their analysis have been studied(Gupta, Paluru, Nankani, Kulkarni, & Awasthi, 2024).

Material and techniques

To ensure a proper desire for research and impartiality in the assessment system, peer-reviewed articles were reviewed in accordance with the protocol's inclusion standards. A seek model was created, taking into account the hunt phrases and the database searched. The criteria for inclusion in the review were:

1. Study Focus: Studies that check out electrocardiography (ECG) techniques implemented for Coronary Artery Disease (CAD) prediction/detection, and research that involves employing Artificial Intelligence approaches (e.g., deep learning, machine learning and neural networks) in conjunction with ECG for CAD.

2. Publication Type: Studies published in English and peer-reviewed journal articles.

3. Publication Date: Studies published between 2010 and 2025.

Exclusion criteria were:

1. Studies focusing exclusively on different diagnostic tools (e.g., angiography, echocardiography, CT scans) without involving ECG.

Electrocardiography Techniques

One of the advantages of ECG (used for diagnosing heart conditions) is that it is a non-invasive cardiac test(Muzammil et al., 2024), and the 12-lead ECG is the most preferred. Worldwide, it is estimated that more than 300 million ECGs are performed annually(Chang, 2022). The conventional examination involves 12 skin patches called electrodes. Electrical signals from the heart muscle, known as the myocardium, are detected by the sensors placed on the body. In everyday cardiac contraction, the electrical pathway contains a pattern that includes the P wave, the QRS complex, and the T wave. The P wave occurs due to atrial depolarization, the QRS complex is due to ventricular depolarization, and the T wave is due to ventricular repolarization. This event is observed through ventricular repolarization, followed by ventricular contraction, which is displayed via the P, QRS, and T waves(Odinaka et al., 2012). The electrical impulses of the heart govern its rate of contraction and relaxation, resulting in distributed voltage differences on the skin. Electrodes are inserted in specific regions to record variations in the heart's electrical activity, coupled with a 12-lead electrocardiogram. The subsequent waveforms represent the phases of polarization and repolarization of the atrial and ventricular cells, respectively, corresponding to specific stages of the cardiac cycle, as illustrated in Figure 1.

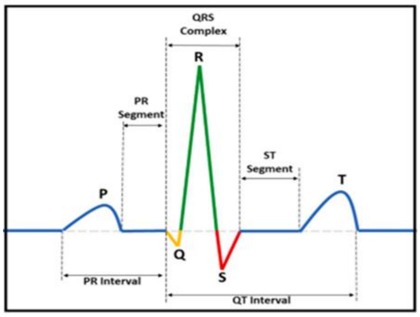

Figure. 1. *Waveform depicting important components of a widespread Electrocardiogram, broadly speaking showing atrial depolarization, ventricular depolarization, and repolarization.*

ECG waveform of a standard heartbeat for the duration of a rotation. It comprises T and P waves, QRS complex, QT interval, ST segment, PR segment and PR interval(Mao, Li, Li, & Li, 2023). To explain the depolarization and repolarization techniques resulting from various feedback variables, six points were recorded using electrodes situated at the extremities (unipolar and bipolar peripheral leads), and another six points were recorded using electrodes located in the precordial area. Abnormalities in the ECG can be used to detect a wide range of cardiovascular diseases, including conduction errors, cardiac arrhythmias, myocardial infarcts, dystonia, cardiomyopathies, and pericarditis. Ergo, precisely decoding an ECG is a critical responsibility in cardiovascular disease, and Table 1 illustrates the characteristics of ECGs in various cardiovascular conditions(Di Costanzo et al., 2024),(Muzammil et al., 2024). Therefore, it is crucial to consider morphological issues to determine the type of algorithms required for green scientific research in ECG evaluation and prognosis. Understanding what a normal heart rhythm is should be prioritized. By satisfying four criteria — heart Rate, starting place, pathway, and speed —a normal rhythm can be identified. The time durations between these waves can indicate the cardiac conduction device, and the period of R-R can be utilized to determine the heart rate(Gupta et al., 2024). An ECG provides a correct assessment of heart rhythm disorders (since it records the heart's electrical activity) and offers a clear image of the electrical signals to assess the risk of cardiac events and facilitate continuous monitoring. A particular case of single heartbeat arrhythmia may not have a significant impact on our lives, but when arrhythmias occur repeatedly, they may indicate a dangerous condition(Panganiban, Paglinawan, Chung, & Paa, 2021).

Table 1: *ECG characteristics in different cardiovascular conditions.*

Cardiovascular Condition	Common ECG Features
Atrial Fibrillation (AF)	- Absence of P-waves
	- Irregularly irregular R-R intervals
	- Fibrillatory waves (f-waves) instead of P-waves
Myocardial Infarction (MI)	- ST-segment depression or elevation
	- ST-segment elevation (STEMI)
	- ST-segment depression (NSTEMI)
	- T-wave inversion
	- Q-waves (pathological Q-waves)
Atrial Flutter	- Sawtooth-shaped flutter waves (F-waves)
	- Regular R-R intervals (2:1, 3:1, etc.)
	- ST-segment changes (often with rapid ventricular response)
Ventricular Tachycardia (VT)	- Wide QRS complexes (>0.12 s)
	- Absence of P-waves before QRS complexes
	- Regular or irregular rhythm
Ventricular Fibrillation (VF)	- Chaotic and irregular QRS complexes
	- Absence of P-waves and T-waves
	- "Quivering" appearance of the ECG trace

Electrocardiographic Techniques for Coronary Artery Disease Detection.

By placing electrodes at specific locations on the chest, the electrocardiogram records changes in electric potentials at these locations, resulting from the heart's rhythm(ISLAM, DAS, HIROSE, & MOLLA, 2012). The ECG may identify each coronary heart pulse as a sequence of deflections that are slightly different from the baseline. Muscular contraction, which occurs due to the temporal development of electrical action in the heart, is reflected in these deflections. The three most essential elements that can be learn from the ECG signal are the T and P waves, and the QRS complex. Ischemia typically manifests as T-wave abnormalities and/or ST-segment aberrations in the ECG signal. The spontaneous prognosis of coronary insufficiency, primarily based on the electrocardiogram rhythm, contains phases, such as myocardial beat and ischemic episode detection. A ST-segment morphological change associated with hypoperfused (ischemic) alterations is often detected by long-period ECG monitoring, typically including 24 hours of continuous monitoring. Ischemia alters the electrical cardiac rhythm (ECG) signal .

Thus, the ST-T complex wave shape is often affected, as demonstrated in studies that use remote characteristics (T wave level, ST-J amplitude, and ST slope), leading to inadequate assessment. Heart Rate Variability (HRV) is an evaluation of the differences in the immediate heartbeat charge phase, utilizing the beat-to-beat RR intervals(Kamaruddin, Murugappan, & Omar, 2012),(Huang et al., 2022). To diagnose cardiac conditions, it is necessary to evaluate the heart's condition. The sinoatrial node, also known as the heart's natural pacemaker, generates electrical impulses that travel through the heart muscle, causing it to contract and pump blood. These impulses can be identified using an ECG, which measures the electrical function of the heart. The technology utilizes this information to identify the heart's status, including its location, chamber size, beat and rhythm, as well as the presence of any cardiac injury(Payne, Zeigler, & Gillette, 2011).

Artificial Intelligence in cardiovascular medicine

Nowadays, AI can be employed in various aspects of science (including medicine) due to significant improvements in computing technology. Unique angles were included, such as health record assessment, analysis, imaging, treatment program guidance, and early detection of potential health issues(Argentiero et al., 2022). Furthermore, since cardiovascular diseases are a burden to international healthcare, AI has the potential to be utilized in such cases, such as coronary artery disease, valvular heart disease, electrophysiology, and coronary heart failure. Employing learning for self-networks of neurons in electrocardiography is the earliest of these bundles. Researchers have investigated the general efficacy of self-mastering neural networks in identifying patterns in electrocardiograms and recognizing distinct types of cardiovascular arrhythmias. It was found that further development is required before employing these networks in more complex areas. Therefore, significant improvements and expansions in the AI devices' capabilities were conducted, including cardiac/coronary and echocardiography applications(Roth et al., 2020).

Integration of Artificial Intelligence with ECG and Prediction and Detection of Coronary Artery Disease

Artificial Intelligence (AI) emulates the human brain to analyze data (Singh et al. 2024). AI involve various techniques such as natural language processing (NLP), deep learning (DL) and machine learning (ML). Machine learning procedures are an approach in which the computer learns best after receiving human feedback. The existence of existing records is a precondition for the use of generation. The device is initially fed data and classified before learning to classify current facts by type. The system subsequently executes its scheduled tasks in accordance with its intended tasks. Following an initial phase of the software, the array set restrictions are enhanced by human input, revealing both incorrect and correct categorizations to the tool. In the case of DL, mainly oriented records are unnecessary. DL systems generate pictures using multiple neural networks that include several algorithms and are model after the human brain. Thus, they enable the machine to process unstructured statistics.(Singh et al., 2024),(Voulodimos, Doulamis, Doulamis, & Protopapadakis, 2018)

This advancement has led to automatic AI systems that resemble human analysis of the ECG, with theoretically higher indicative consistency and processing performance than outdated rule-based computer interpretation(Salam & Abhinesh, 2024). Even though the recording of the ECG is reproducible and well standardized, the accuracy of a human interpreter varies substantially depending on their experience and understanding. For many years, computer-generated interpretations were used in this scenario. However, these conclusions are based on predefined regulations and guiding patterns, or feature reliability algorithms, which can occasionally fail to capture the complexities and intricacies of an ECG(Siontis, Noseworthy, Attia, & Friedman, 2021).

ECG analysis employs various AI methodologies, which present distinct benefits and limitations(Lecun, Bengio, & Hinton, 2015). Nevertheless, convolutional artificial neural networks (CNNs), which are a form of deep learning, have been broadly used in voice recognition, image processing and computer vision, and can now be applied to assess the standard 12 leads(Siontis et al., 2021). CNNs are renowned for their ability to analyze nested feature representations from meticulously organized raw input and image data. They enable systems to be formidable in form and predictive duties without the necessity for mechanical derivation of portions of the ECG, such as multiple periods or amplitudes(Lecun et al., 2015). CNNs are broadly utilized in all adult and pediatric electrocardiogram (pECG) assessments. For example, a CNN-based prediction model (called CHDdECG) was developed by Chen et al. It improves the precision of congenital coronary artery condition identification by combining wavelet attributes, human-idea competences, and raw waveform characteristics(J. Chen et al., 2024). Such a procedure displays how incorporating multiple trait types into a CNN structure can enhance the model's behavior. Although Long Short-Term Memory networks (LSTMs), recurrent neural networks, and RNNs are designed for sequential data, they are also capable of capturing temporal relationships in time-series data, such as ECGs. Composition approaches (including random forests) and Support vector machines (SVMs) were also used for category duties, providing advantages in comprehension and performance in general with smaller datasets. Another powerful ensemble learn algorithm is XGBoost (extreme gradient boosting), which has demonstrated potential in ECG interpretation(T. Chen & Guestrin, 2016). XGBoost extends gradient boosting by cultivating a set of selection trees that gradually enhance predictions. Because of the limitations of employing ECG data, models that involve SVMs or random trees do not have the same level of consistency as neural networks with deep connections, and as a result, are not frequently employed for this purpose(Leone, O'Sullivan, & Bravo-Jaimes, 2025). Latest improvements in AI technologies, specifically deep learning-based ECG interpretation, have displayed potential in surpassing those limitations(Avula, Wu, & Carrick, 2023),(Siontis et al., 2021). AI-based techniques extend beyond traditional diagnostic uses, detecting conditions such as left ventricular dysfunction and predicting future cardiovascular events, including atrial fibrillation(Attia, Harmon, Behr, & Friedman, 2021), it is suggested that AI-based ECG analysis may be able to detect non-specific/subtle changes in stable angina, thus enhancing the prediction of obstructive CAD(Park et al., 2024). ECG-AI algorithms, designed to perceive CAD, can offer formerly unavailable insights into CAD danger assessments. As a result, they can be an effective tool for forecasting the hazard of myocardial infarction(Sun, Yin, Yang, & Huo, 2023). The feasibility of accurately detecting coronary CAD, as validated by angiography, was evaluated using a deep learning AI model in conjunction with a 12-lead ECG. Based on photo statistics obtained from the ECG, an ECG-based AI may also be capable of determining which coronary artery is stenotic or blocked, provided the correct AI learning model is used(Huang et al., 2022). ECG deep-learning to know models are increasingly more directed at clinically applicable endpoints and feature demon started incredible performance over an extensive variety of diagnostic and predictive functions; however, the models investigated, CNNs, and others are computationally demanding in terms of education. The discipline of ECG deep learning could benefit from adhering to a standardized set of medical reporting guidelines. Their reporting is enormously variable, but few courses offer the means for methodological reproduction or model checking with the aid of external agencies(Voulodimos et al., 2018),(Avula et al., 2023).

Conclusion

In conclusion, ECG screening remains an essential tool for the early detection of CAD due to its accessibility and diagnostic price. However, its sensitivity in figuring out early or subtle ischemic changes is limited. The integration of AI enhances ECG interpretation by enabling more accurate detection of CAD-related patterns and danger stratification. AI-assisted ECG represents a promising advancement in cardiovascular diagnostics, requiring thorough clinical validation for effective implementation. Nonetheless, further large-scale scientific trials and external validation research are critical to establishing the robustness and generalizability of the suggested AI models across medical environments.

REFERENCES

Achim, A., Péter, O. Á., Cocoi, M., Serban, A., Mot, S., Dadarlat-Pop, A., … Ruzsa, Z. (2023). Correlation between Coronary Artery Disease with Other Arterial Systems: Similar, Albeit Separate, Underlying Pathophysiologic Mechanisms. *Journal of Cardiovascular Development and Disease*, *10*(5). https://doi.org/10.3390/jcdd10050210

Argentiero, A., Muscogiuri, G., Rabbat, M. G., Martini, C., Soldato, N., Basile, P., … Guaricci, A. I. (2022). The Applications of Artificial Intelligence in Cardiovascular Magnetic Resonance—A Comprehensive Review. *Journal of Clinical Medicine*, *11*(10), 1–18. https://doi.org/10.3390/jcm11102866

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/ehab649

Avula, V., Wu, K. C., & Carrick, R. T. (2023). Clinical Applications, Methodology, and Scientific Reporting of Electrocardiogram Deep-Learning Models: A Systematic Review. *JACC: Advances*, *2*(10). https://doi.org/10.1016/j.jacadv.2023.100686

Chang, R. K. (2022). Resting 12-lead ECG tests performed by patients at home amid the COVID-19 pandemic — Results from the first 1000 patients. *Journal of Electrocardiology*, *73*(July), 108–112. https://doi.org/10.1016/j.jelectrocard.2022.06.006

Chen, J., Huang, S., Zhang, Y., Chang, Q., Zhang, Y., Li, D., … Liang, H. (2024). Congenital heart disease detection by pediatric electrocardiogram based deep learning integrated with human concepts. *Nature Communications*, *15*(1). https://doi.org/10.1038/s41467-024-44930-y

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, *13-17-Augu*, 785–794. https://doi.org/10.1145/2939672.2939785

Di Costanzo, A., Spaccarotella, C. A. M., Esposito, G., & Indolfi, C. (2024). An Artificial Intelligence Analysis of Electrocardiograms for the Clinical Diagnosis of Cardiovascular Diseases: A Narrative Review. *Journal of Clinical Medicine*, *13*(4). https://doi.org/10.3390/jcm13041033

Di Lenarda, F., Balestrucci, A., Terzi, R., Lopes, P., Ciliberti, G., Marchetti, D., … Conte, E. (2024). Coronary Artery Disease, Family History, and Screening Perspectives: An Up-to-Date Review. *Journal of Clinical Medicine*, *13*(19). https://doi.org/10.3390/jcm13195833

Duncker, D., Ding, W. Y., Etheridge, S., Noseworthy, P. A., Veltmann, C., Yao, X., … Gupta, D. (2021). Smart wearables for cardiac monitoring—real-world use beyond atrial fibrillation. *Sensors*, *21*(7), 1–25. https://doi.org/10.3390/s21072539

Gupta, U., Paluru, N., Nankani, D., Kulkarni, K., & Awasthi, N. (2024). A comprehensive review on efficient artificial intelligence models for classification of abnormal cardiac rhythms using electrocardiograms. *Heliyon*, *10*(5), e26787. https://doi.org/10.1016/j.heliyon.2024.e26787

Hosseini, K., Mortazavi, S. H., Sadeghian, S., Ayati, A., Nalini, M., Aminorroaya, A., … Kamangar, F. (2021). Prevalence and trends of coronary artery disease risk factors and their effect on age of diagnosis in patients with established coronary artery disease: Tehran Heart Center (2005–2015). *BMC Cardiovascular Disorders*, *21*(1), 1–11. https://doi.org/10.1186/s12872-021-02293-y

Huang, P. S., Tseng, Y. H., Tsai, C. F., Chen, J. J., Yang, S. C., Chiu, F. C., … Tsai, C. T. (2022). An Artificial Intelligence-Enabled ECG Algorithm for the Prediction and Localization of Angiography-Proven Coronary Artery Disease. *Biomedicines*, *10*(2). https://doi.org/10.3390/biomedicines10020394

ISLAM, M. R., DAS, S., HIROSE, K., & MOLLA, M. K. I. (2012). Analysis of Ecg Signals Using Data-Adaptive Time Domain Filtering for Cardiovascular Disease Diagnosis. *Advances in Adaptive Data Analysis*, *04*(01n02), 1250006. https://doi.org/10.1142/s1793536912500069

Kamaruddin, N. H., Murugappan, M., & Omar, M. I. (2012). Early prediction of Cardiovascular Diseases using ECG signal: Review. *SCOReD 2012 - 2012 IEEE Student Conference on Research and Development*, (April), 48–53. https://doi.org/10.1109/SCOReD.2012.6518609

Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Leone, D. M., O'Sullivan, D., & Bravo-Jaimes, K. (2025). Artificial Intelligence in Pediatric Electrocardiography: A Comprehensive Review. *Children*, *12*(1), 1–18. https://doi.org/10.3390/children12010025

Mao, J., Li, Z., Li, S., & Li, J. (2023). A Novel ECG Signal Denoising Algorithm Based on Sparrow Search Algorithm for Optimal Variational Modal Decomposition. *Entropy*, *25*(5). https://doi.org/10.3390/e25050775

Muzammil, M. A., Javid, S., Afridi, A. K., Siddineni, R., Shahabi, M., Haseeb, M., … Nashwan, A. J. (2024). Artificial intelligence-enhanced electrocardiography for accurate diagnosis and management of cardiovascular diseases. *Journal of Electrocardiology*, *83*(January), 30–40. https://doi.org/10.1016/j.jelectrocard.2024.01.006

Odinaka, I., Lai, P. H., Kaplan, A. D., O'Sullivan, J. A., Sirevaag, E. J., & Rohrbaugh, J. W. (2012). ECG biometric recognition: A comparative analysis. *IEEE Transactions on*

Information Forensics and Security, *7*(6), 1812–1824. https://doi.org/10.1109/TIFS.2012.2215324

Panganiban, E. B., Paglinawan, A. C., Chung, W. Y., & Paa, G. L. S. (2021). ECG diagnostic support system (EDSS): A deep learning neural network based classification system for detecting ECG abnormal rhythms from a low-powered wearable biosensors. *Sensing and Bio-Sensing Research*, *31*(November 2020). https://doi.org/10.1016/j.sbsr.2021.100398

Park, J., Kim, J., Kang, S. H., Lee, J., Hong, Y., Chang, H. J., … Yoon, Y. E. (2024). Artificial intelligence–enhanced electrocardiography analysis as a promising tool for predicting obstructive coronary artery disease in patients with stable angina. *European Heart Journal - Digital Health*, *5*(4), 444–453. https://doi.org/10.1093/ehjdh/ztae038

Payne, L., Zeigler, V. L., & Gillette, P. C. (2011). Acute cardiac arrhythmias following surgery for congenital heart disease: Mechanisms, diagnostic tools, and management. *Critical Care Nursing Clinics of North America*, *23*(2), 255–272. https://doi.org/10.1016/j.ccell.2011.04.001

Roth, G. A., Mensah, G. A., Johnson, C. O., Addolorato, G., Ammirati, E., Baddour, L. M., … Fuster, V. (2020). Global Burden of Cardiovascular Diseases and Risk Factors, 1990-2019: Update From the GBD 2019 Study. *Journal of the American College of Cardiology*, *76*(25), 2982–3021. https://doi.org/10.1016/j.jacc.2020.11.010

Salam, A., & Abhinesh, N. (2024). Revolutionizing dermatology: The role of artificial intelligence in clinical practice. *IP Indian Journal of Clinical and Experimental Dermatology*, *10*(2), 107–112. https://doi.org/10.18231/j.ijced.2024.021

Sayols-Baixeras, S., Lluís-Ganella, C., Lucas, G., & Elosua, R. (2014). Pathogenesis of coronary artery disease: Focus on genetic risk factors and identification of genetic variants. *Application of Clinical Genetics*, *7*, 15–32. https://doi.org/10.2147/TACG.S35301

Singh, M., Kumar, A., Khanna, N. N., Laird, J. R., Nicolaides, A., Faa, G., … Suri, J. S. (2024). Artificial intelligence for cardiovascular disease risk assessment in personalised framework: a scoping review. *EClinicalMedicine*, *73*(January), 102660. https://doi.org/10.1016/j.eclinm.2024.102660

Siontis, K. C., Noseworthy, P. A., Attia, Z. I., & Friedman, P. A. (2021). Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. *Nature Reviews Cardiology*, *18*(7), 465–478. https://doi.org/10.1038/s41569-020-00503-2

Sun, X., Yin, Y., Yang, Q., & Huo, T. (2023). Artificial intelligence in cardiovascular diseases: diagnostic and therapeutic perspectives. *European Journal of Medical Research*, *28*(1), 1–11. https://doi.org/10.1186/s40001-023-01065-y

Voulodimos, A., Doulamis, N., Doulamis, A., & Protopapadakis, E. (2018). Deep Learning for Computer Vision: A Brief Review. *Computational Intelligence and Neuroscience*, *2018*. https://doi.org/10.1155/2018/7068349