Enhanced Coronary Artery Disease Diagnosis and Progression Tracking using Artificial Intelligence

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Abstract **– This research focuses on the use of Artificial Intelligence (AI) powered techniques for enhanced coronary artery disease diagnosis (CAD) and progression tracking. According to World Health Organisation (2021), CAD is a major contributor to morbidity and mortality globally. Effective treatment and management of CAD depend on an early diagnosis and ongoing monitoring. Unfortunately, there are still issues with existing diagnostic techniques that make it difficult to identify CAD in a timely and reliable manner, and monitoring the disease's evolution over time is still difficult. In this research we developed an AI-based model that automate CAD diagnosis and progression tracking using image analysis and evalution of key biomarkers. The solution allows user to capture 11 patient attributes and implements the deep neural network (DNN) algorithm to classify the patient as having CAD or not. The DNN based model was trained using 80% of the 70 000 clinical instances from the CAD dataset and 20% of the records were used for testing. The second CAD diagnosis component in the solution evaluates three biomarkers (c-reactive protein, troponin and homocysteine) and classify the patient results as either CAD positive or negative. This solution also does image analysis of coronary artery images to check for plaque using a convolutional neural network (CNN) based model. This component of the solution allows for CAD progression tracking in a patient. The system achieved an overall accuracy of 95.1%, specificity of 96.3% and sensitivity of 95.4% which shows high performance when compared to similar CAD diagnosis models. AI algorithms used in this research have shown superior accuracy in diagnosing CAD, surpassing existing diagnostic methods. This enhancement is crucial for early detection and intervention, ultimately reducing the risk of severe complications and mortality associated with CAD. Key recommendations include adoption of AI technologies in clinical workflow by healthcare centers, use of wearable devices for real time monitoring of patients and advanced data integration.**

Keywords **– Artificial Intelligence, biomarker, coronary artery disease, deep neural network.**

I. INTRODUCTION

Coronary artery disease (CAD) is responsible for a significant number of events, including heart attacks and deaths, which impose a substantial burden on individuals and healthcare systems worldwide (MedlinePlus, n.d.; Benjamin et al., 2019). Globally, cardiovascular diseases (CVDs) are the primary cause of death. 32% of all fatalities worldwide in 2019 were attributed to CVDs, with an estimated 17.9 million deaths. Heart attacks and strokes were the cause of 85% of these fatalities. More than 75% of deaths from CVD occur in low- and middle-income nations. According to the World Health Organisation (2021), 38% of the 17 million premature deaths (those under 70 years old) resulting from noncommunicable diseases in 2019 were attributable to CVDs. By addressing behavioural and environmental risk factors such air pollution, bad diets and obesity, physical inactivity, hazardous alcohol consumption, and tobacco use, most cardiovascular illnesses can be avoided. Early detection of cardiovascular illness is crucial for managing it with medication and counselling.

In the realm of cardiovascular medicine, CAD stands as a leading cause of mortality worldwide, underscoring the urgency for improved diagnostic and monitoring methodologies (Infante et al, 2021). Identification of the relevant biomarkers of CAD and accurate image analysis accelerates the diagnosis and progression tracking of the disease. AI algorithms have shown the potential to uncover the right balance of biomarkers and accurate images analysis, thereby offering unprecedented opportunities for disease detection, diagnosis, and prognosis (Sun et al., 2023). In this research we propose to leverage AI algorithms to discover the right biomarkers and automate image analysis in CAD diagnosis and disease progression tracking.

II. SIMILAR RESEARCHES

Panteris et al. (2022) created a Machine Learning (ML) predictive model that utilises metabolic and clinical data to estimate the severity of CAD using the SYNTAX score. In this study, analytical techniques were created to measure the quantities of particular ceramides, fatty acids, acyl-carnitines, and proteins like adiponectin, galectin-3, and the APOB/APOA1 ratio in the serum blood. Two categories of patients were identified: non-obstructive CAD (SS = 0) and obstructive CAD (SS > 0). In order to identify individuals at high risk for complex CAD, a risk prediction algorithm (boosted ensemble algorithm XGBoost) was developed by combining clinical parameters with both known and unknown biomarkers. The XGBoost algorithm's performance was measured with an AUC of 0.725 (95% CI: 0.691–0.759). Thus, a machine learning model that includes clinical features in addition to specifics.

The study by Oikonomou et al. (2019) offers an AI-powered technique to analyse the radiomic profile of coronary perivascular adipose tissue (PVAT) in order to predict cardiac risk. In the first study, radiomic characteristics generated from tissue CT scans were correlated with the expression of genes encoding inflammation, fibrosis, and vascularity in adipose tissue biopsies taken from 167 patients having heart surgery. A machine learning (random forest) algorithm (fat radiomic profile, FRP) was trained and validated in the second study using 1391 coronary PVAT radiomic features in 101 patients who had major adverse cardiac events (MACE) within 5 years of a CCTA and 101 matched controls. This allowed the algorithm to distinguish between cases and controls (C-statistic 0.77 [95%CI: 0.62–0.93] in the external validation set). this study did not analyse FRP surrounding the left circumflex coronary artery because of its varied morphology. Intraoperative radiography studies (Johnson et al, 2019) may be needed to better characterize the association of PVAT radiome with coronary atherosclerosis phenotype.

Research by (Abdar et al, 2022) focusing on computer methods and programs in biomedicine proposed pre-processing with data manipulation and normalization, optimization of classifier parameters using GA and PSO algorithms. In terms of its strengths the model achieved N2Genetic-nuSVM achieved 93.08% accuracy and 91.51% F1-score. However developed model needs more data for testing and GA and PSO methods are time-consuming.

(Gautam et al, 2022), made a review of current and future applications of AI in CAD. Their study did a systematic review of the advances in AI relating to coronary artery disease, current limitations, and future perspectives. Quite a number of advances were discovered notably, enhanced accuracy in CAD prediction and provision of tools to focus on individualized yet comprehensive and precise care. Although reviewed AI based methods have shown improved CAD diagnosis compared to most traditional methods there still exits some limitations such as, overfitting encountered during ML model development and lack of external validity due to use of smaller datasets to train model.

An in-depth overview of artificial intelligence (AI) applications in image-based cardiovascular disease (CVD) analysis is presented in a survey by Wang and Zhu (2015), which also provides insights into the field's potential for the future. The research methodically groups the literature according to the main anatomical structures associated with cardiovascular disease (CVD), distinguishing between non-vessel structures (like ventricles and atria) and vessel structures (like the aorta and coronary arteries). This classification offers an organised method to investigate different imaging modalities, such as Magnetic Resonance Imaging (MRI), which is frequently employed in cardiovascular disease research. The review of these modalities is part of the study, which provides a comprehensive picture of the various imaging approaches combined with AI for CVD analysis. It also offers an inventory of publicly available cardiac image datasets and code repository.

(Infante et al., 2021) conducted a systematic study of radiogenomics and artificial intelligence (AI) techniques applied to cardiac magnetic resonance imaging and cardiac computed tomography angiography for precision medicine in coronary heart disease. The goal of the study was to examine how technological advancements in medical imaging, specifically in cardiac CT angiography and cardiac magnetic resonance protocols, have paved the way for the discipline of radiogenomics. The goal of

radiogenomics is to find the best radiomic/biomarker signatures by integrating a vast array of imaging features and molecular profiles. Furthermore, various layers of data (imaging parameters and features, clinical variables, and biomarkers) may be combined by supervised and unsupervised artificial intelligence algorithms to create intricate and specialised coronary heart disease (CHD) risk models, which would enable more precise diagnosis and dependable prognosis predict. There are still problems with the integration of AI-based techniques, radiogenomics, and radiomics into clinical practice, despite these promising developments in the diagnosis and characterisation of congenital heart disease (CHD) and patient outcome prediction.

Artificial intelligence (AI) techniques have the potential to speed up the diagnosis and treatment of cardiovascular diseases (CVDs), such as heart failure, atrial fibrillation, valvular heart disease, hypertrophic cardiomyopathy, congenital heart disease, and so forth, according to the study "Artificial intelligence in cardiovascular diseases: diagnostic and therapeutic perspectives" by Sun et al. (2023). AI has shown to be a useful tool for diagnosing CVD, improving the efficacy of auxiliary instruments, classifying and stratifying diseases, and predicting outcomes. New artificial intelligence (AI) algorithms are intended to handle even more difficult jobs than conventional approaches. These algorithms are deeply developed to capture tiny correlations from vast amounts of healthcare data.

The paper presented recent uses of AI in CVDs, which may help doctors with little background in computer science comprehend the field's boundary and apply AI algorithms to clinical settings. It has been demonstrated that AI-based models function well when assessing prognosis in CAD patients. Artificial Intelligence is another new technology that can help anticipate risks more accurately both before and after heart surgery.

III. RESEARCH METHODOLOGY

This research follows the DSR phases that starts with the identification of the problem (increasing prevalence of CAD and the limitations of current diagnostic methods) and motivation (the need for more accurate, efficient, and non-invasive diagnostic tools). In the second phase we clearly define the objectives we have set out to achieve the solution. The objectives of the project are to diagnose and track progression of CAD using an AI based model, to evaluate the model's diagnostic capabilities of the tool and to integrate the model with existing healthcare infrastructure for seamless CAD diagnosis and progression tracking

The third phase takes us through design and development. This entails coming up with a comprehensive system architecture for the AI system, algorithm development and prototype creation. In the fourth phase the AI based solution is demonstrated through pilot testing using data from a selected dataset. Evalution of the solution is done in the fifth phase of the DSR using results obtained in the pilot test. A set of performance metrics are defined and used to evaluate the solution’s accuracy and effectiveness. Finally, the findings of the research can be communicated through publishing in academic journals or stakeholder engagement.

A. Data Sources

The AI based CAD diagnosis system model was trained and tested using the cardiovascular disease dataset from kaggle.com that consists of 70 000 records of patient data, 11 features plus target. The dataset has three types of input features: objective (factual information), examination (results of medical examination) and subjective (information given by the patient). The dataset will be split into 80% training records and 20% testing records. The Deep Neural Network (DNN) based model learns to identify a target associated with a specific combination of input features through training it goes through using the training records (80% of the dataset). The validation of the ability of the model to correctly identify a target from a given set of input features is done using testing records (20% of the dataset).

The second model used in the system is Convolutional Neural Networks (CNN) based model to classify coronary CT images using the amount and place of coronary stenosis. The model allows for automatic classification of patients for the presence of functionally significant stenosis in one or more coronaries. The model used the CaDEX dataset on kaggle.com that contains 1300 coronary CT images for training and testing. The dataset will be split the dataset

into training images (80% of the dataset) and (20% of the dataset). This model will help in CAD progression tracking and enhancing its diagnosis.

To enhance the diagnostic capabilities the model is complemented by a tree-based machine learning algorithm (XGBoost) that evaluates the contribution of three other key biomarkers (C-reactive protein, Troponin and Homocysteine). XGBoost was chosen for its improved performance and its ability to reduce overfitting (Martínez-Muñoz, no. date). Data on these three biomarkers is obtained from the tests that are performed on a patient during medical examination, these are not part of the input features of cardiovascular disease dataset used in the model. Simulated data on these three biomarkers will be used for training and validating the algorithm.

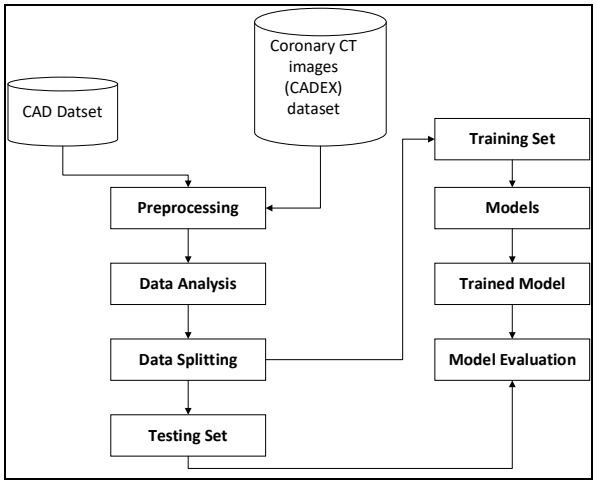

Fig. 1. Training and Testing models with respective datasets

B. Data Methodology

The CAD dataset with patient data used for training and testing AI based CAD diagnosis model was chosen because of the huge number of patient records (70 000) in contains. The model accuracy, specificity, and sensitivity were enhanced by making use of this huge dataset. The system's CAD diagnosis is also enhanced through evaluation of three other biomarkers (CRP, Troponin and Homocysteine) which are not part of the CAD dataset. A tree-based machine learning algorithm (XGBoost) is used to analyse the results of these three biomarkers and the outcome is used by experts together with the output of the model to determine the CAD diagnosis result. The third component of the system is a model that analyse CT images and allows for automatic classification of patients for the presence of functionally significant stenosis in one or more coronaries. This model was trained and validated using CT images in the CaDEX dataset. When in use, the system allows users to input patient data with 11 features, three biomarkers (CRP, Troponin, and Homocysteine) and CT images. The architecture of the system with data flows is illustrated in Fig. 2 that follows.

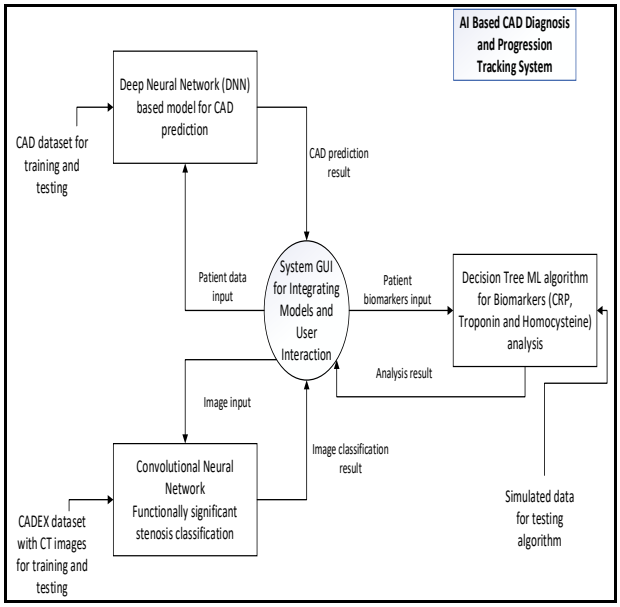

Fig. 1. System Architecture diagram

C. Modelling

Based on a deeper multilayer perceptron with additional hidden layers and regularisation, dropout, and non-linear transfer functions, the DNN based classification model uses a sigmoid function for binary classification utilising deep learning techniques. The model's structural description is depicted in Figure 3.3 below. The deep neural network prediction model received an input data matrix containing 12 heart disease attributes and 56 000 clinical cases at the same time. The model propagated all CAD input patterns to identify all unit outputs of both linear and non-linear transfer functions.

In addition to allowing for the modification of a set of hyperparameters, a hyper-parameter turning and control block also managed the batch size and the number of epochs used in the deep neural network classification model's training. In deep learning, the number of epochs denotes the total number of times that all training data are processed by the learning

algorithm in order to modify the weights of the deep neural networks. Errors were identified throughout the training process of the deep neural network classification model by comparing all unit outputs with the target variable class's desired pattern responses for coronary heart disorders. The hyper-parameter compounded the error further before the learning algorithm block made adjustments.

Following the minimization of error at each stage, the weights in the deep neural network classification model were updated using unit weight adjustment. In this process, the input data and corresponding target variable data were used to train the deep neural network model until it approximated a function within a previously defined error value. Until the whole number of epochs was used, or until the sum of squared errors was minimised to the lowest value below the previously established error value, this training procedure was repeated. The final weights were fed into the deep neural network prediction model, also referred to as the diagnostic model, once the training for the DNN classification model was finished. Then, CAD patterns were identified and diagnosed using the DNN prediction model.

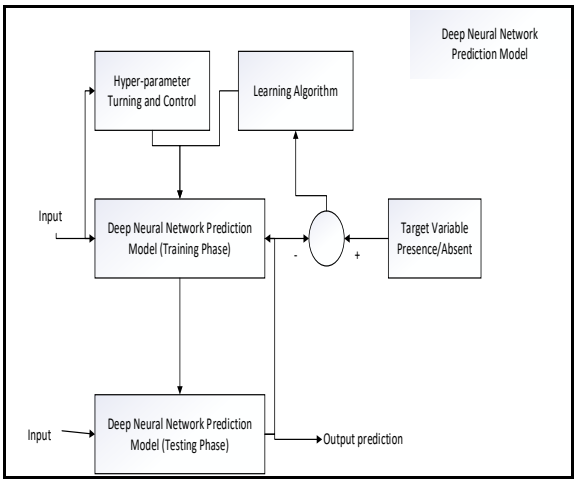

Fig. 1. Deep neural network model

IV. EVALUATION EQUATIONS

The models' performance was assessed using three criteria: specificity, sensitivity, and accuracy. The two models used in the CAD diagnosis and progression tracking system were evaluated using test clinical instances from the corresponding datasets. The evaluation method known as accuracy is used to calculate the proportion of instances that the models accurately predict. This equation can be used to express the accuracy.

$$\text{Accuracy} = \frac{Tp+Tn}{Tp+Tn+Fp+Fn} \quad (1)$$

The following formula is used to express specificity, which is the percentage of CAD-negative patients that the models accurately predicted.

$$\text{Specificity} = \frac{Tp}{Tn+Fp} \quad (2)$$

The sensitivity, which is represented by the following equation, indicates the proportion of CAD-positive patients that the models accurately predicted:

$$\text{Sensitivity} = \frac{Tp}{Tp+Fn} \quad (3)$$

where the false positive is denoted by *Fp*, the false negative by *Fn*, and the genuine positive by *Tp* whilst the genuine negative by *Tn*.

The AI based CAD diagnosis and progression tracking algorithms were implemented using python programming language using the Vertex AI machine learning development platform provided by Google Cloud. Integration of the models with an GUI that facilitate the use of the models in healthcare management system was done using Taipy language. The user interface dashboard of the system is illustrated in the wireframe diagram in Fig. 3 below.

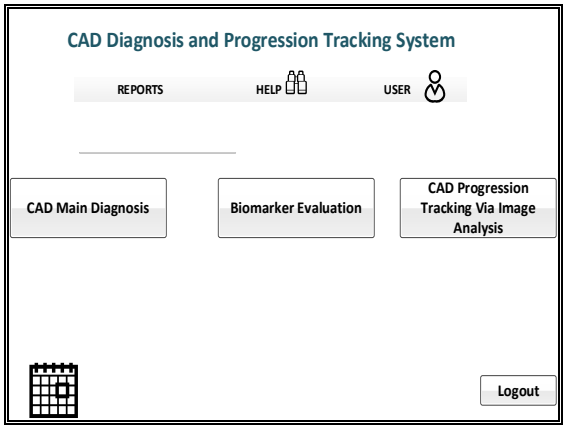

Fig. 1. Wireframe of the system dashboard

V. RESULTS AND DISCUSSION

The findings show how AI-driven approaches can improve clinical outcomes for patients with CAD and their potential impact. In particular, we report on the outcomes of diagnosing and tracking the course of CAD using the DNN, CNN, and XGBoost algorithms. The evalution of the DNN based model, CNN based model and XGBoost algorithm used in the CAD diagnosis and progression tracking system was done using three metrics (accuracy, specificity and sensitivity). The evaluation metrics are generated using equations (1), (2) and (3) presented earlier on. The calculated values of each of these metrics for DNN, CNN and XGBoost algorithms are presented in Table 1 below.

TABLE I-ALGORITHM EVALUATION

Algorithm	**Accuracy**	**Specificity**	**Sensitivity**
DNN	0.963	0.987	0.959
CNN	0.950	0.961	0.962
XGBoost	0.940	0.94	0.94
Overall	**0.951**	**0.963**	**0.954**

The system achieved an overall accuracy of 95.1%, specificity of 96.3% and sensitivity of 95.4% which shows high performance when compared to similar CAD diagnosis models. A comparison of the system's performance to the Support Vector Machine (SMV) model and Random Forest (RF) based model which were derived from the research by (Muhammad et al, 2021) which looked at machine learning predictive models for CAD using dataset obtained from two General Hospitals in Kano State, Nigeria shows a superior performance by the proposed model in terms accuracy, specificity and sensitivity. Table 2 below shows the performance statistics of the three models.

TABLE 2-COMPARISON OF PROPOSED MODEL AND TWO OTHER SIMILAR MODELS

	Proposed model	**SMV model**	**RF model**
Accuracy	0.951	0.887	0.92
Specificity	0.963	0.863	0.832
Sensitivity	0.954	0.873	0.865

VI. CONCLUSION AND RECOMMENDATIONS

AI algorithms used in this research have shown superior accuracy in diagnosing CAD, surpassing existing diagnostic methods. This enhancement is crucial for early detection and intervention, ultimately reducing the risk of severe complications and mortality associated with CAD. Key recommendations include adoption of AI technologies in clinical workflow by healthcare centers, use of wearable devices for real time monitoring of patients and advanced data integration.

REFERENCES

[1] Abdar, M. et al. (2019) "A new machine learning technique for an accurate diagnosis of coronary artery disease," Computer Methods and Programs in Biomedicine, 179. Available at: https://doi.org/10.1016/j.cmpb.2019.104992.

[2] Apuke, O.D. (2017) "Quantitative Research Methods: A Synopsis Approach," Kuwait Chapter of Arabian Journal of Business and Management Review, 6(11), pp. 40–47. Available at: https://doi.org/10.12816/0040336.

[3] Bartelt, A., Leipsic, J. and Weber, C. (2019) "The new age of radiomic risk profiling: Perivascular fat at the heart of the matter," European Heart Journal. Oxford University Press, pp. 3544–3546. Available at: https://doi.org/10.1093/eurheartj/ehz717.

[4] Begou, et al. (2021) "Development and Validation of a RPLC-MS/MS Method for the Quantification of Ceramides in Human Serum." J. Chromatogr. B 2021, 1175, 122734, doi:10.1016/j.jchromb.2021.122734.

[5] Bos, S. et al. (2017) "Novel protein biomarkers associated with coronary artery disease in statin-treated patients with familial hypercholesterolemia," Journal of Clinical Lipidology, 11(3), pp. 682–693. Available at: https://doi.org/10.1016/j.jacl.2017.03.014.

[6] Cleve Clin J Med, 56 (1989), pp. 126-130

[7] Cleveland Clinic, (2022), 'Troponin Test', Available at: https://my.clevelandclinic.org/health/diagnostics/22770-troponin-test

[8] Cleveland Clinic, 2023, "Coronary Artery Disease", Available at: https://my.clevelandclinic.org/health/diseases/16898-coronary-artery-disease

[9] El-Bialy, R. et al. (2015) "Feature Analysis of Coronary Artery Heart Disease Data Sets," in Procedia Computer Science. Elsevier, pp. 459–

468. Available at: https://doi.org/10.1016/j.procs.2015.09.132.

[10] El-Bialy, R. et al. (2015) "Feature Analysis of Coronary Artery Heart Disease Data Sets," in Procedia Computer Science. Elsevier, pp. 459–468. Available at: https://doi.org/10.1016/j.procs.2015.09.132.

[11] Freitas, I.A. de et al. (2020) "Novel biomarkers in the prognosis of patients with atherosclerotic coronary artery disease," Revista Portuguesa de Cardiologia. Sociedade Portuguesa de Cardiologia, pp. 667–672. Available at: https://doi.org/10.1016/j.repc.2020.05.010.

[12] Gala, D. et al. (2024) "The Role of Artificial Intelligence in Improving Patient Outcomes and Future of Healthcare Delivery in Cardiology: A Narrative Review of the Literature," Healthcare (Switzerland). Multidisciplinary Digital Publishing Institute (MDPI). Available at: https://doi.org/10.3390/healthcare12040481.

[13] Gala, D. et al. (2024) "The Role of Artificial Intelligence in Improving Patient Outcomes and Future of Healthcare Delivery in Cardiology: A Narrative Review of the Literature," Healthcare (Switzerland). Multidisciplinary Digital Publishing Institute (MDPI). Available at: https://doi.org/10.3390/healthcare12040481.

[14] Gupta, M.D. et al. (2022) "Artificial intelligence in cardiology: The past, present and future," Indian Heart Journal. Elsevier B.V., pp. 265–269. Available at: https://doi.org/10.1016/j.ihj.2022.07.004.

[15] Huang, Y. et al. (2017) "Biomarkers of Cardiovascular Disease," Disease Markers. Hindawi Limited. Available at: https://doi.org/10.1155/2017/8208609.

[16] Infante, T. et al. (2021) "Radiogenomics and Artificial Intelligence Approaches Applied to Cardiac Computed Tomography Angiography and Cardiac Magnetic Resonance for Precision Medicine in Coronary Heart Disease: A Systematic Review," Circulation: Cardiovascular Imaging, 14(12), pp. 1133–1146. Available at: https://doi.org/10.1161/CIRCIMAGING.121.013025.

[17] J., Brocke, J., Hevner, A. and Maedche, A. (2020) "Introduction to Design Science Research," in, pp. 1–13. Available at: https://doi.org/10.1007/978-3-030-46781-4_1.

[18] Jiao, M. et al. (2020) "Identification of Four Potential Biomarkers Associated With Coronary Artery Disease in Non-diabetic Patients by Gene Co-expression Network Analysis," Frontiers in Genetics, 11. Available at: https://doi.org/10.3389/fgene.2020.00542.

[19] Johnson et al. (2019). "Clinical use of intracoronary imaging. Part 2: acute coronary syndromes, ambiguous coronary angiography findings, and guiding interventional decision-making: an expert consensus document of the European Association of Percutaneous Cardiovascular Interventions." Eur Heart J 2019;EPub ahead of print.

[20] Kececi, N. and Abran, A. (no date) An Integrated Measure for Functional Requirements Correctness. Available at: www.lrgl.uqam.ca.

[21] Martínez-Muñoz, G., Bentéjac, C. and Csörg″ O B Gonzalo Martínez-Muñoz, A. (no date) A Comparative Analysis of XGBoost. Available at: https://www.researchgate.net/publication/337048557.

[22] Martín-Ventura, J.L. et al. (2009) Biomarkers in Cardiovascular Medicine, Rev Esp Cardiol.

[23] Meikopoulos, T et al. (2022), "A HILIC-MS/MS Method Development and Validation for the Quantitation of 13 Acylcarnitines in Human Serum." Chem. 2022, 414, 3095–3108, doi:10.1007/s00216-022-03940-9.

[24] Miao, K.H. and Miao, J.H. (2018) Coronary Heart Disease Diagnosis using Deep Neural Networks, IJACSA) International Journal of Advanced Computer Science and Applications. Available at: www.ijacsa.thesai.org.

[25] Muhammad, L.J. et al. (2021) "Machine Learning Predictive Models for Coronary Artery Disease," SN Computer Science, 2(5). Available at: https://doi.org/10.1007/s42979-021-00731-4.

[26] National Heart, Lung and Blood Institute, 2023, "CORONARY HEART DISEASE: What Is Coronary Heart Disease?", Coronary Heart Disease - What Is Coronary Heart Disease? | NHLBI, NIH

[27] Oikonomou et al. (2019), "A novel machine learning-derived radiotranscriptomic signature of perivascular fat improves cardiac risk prediction using coronary CTangiography." European Heart Journal (2019) 40, 3529–3543, doi:10.1093/eurheartj/ehz592.

[28] Panteris, E. et al. (2022) "Machine Learning Algorithm to Predict Obstructive Coronary Artery Disease: Insights from the CorLipid Trial," Metabolites, 12(9). Available at: https://doi.org/10.3390/metabo12090816.

[29] Paul, G and Alam, F. (2021), Role of homocysteine in the development of cardiovascular disease, Nutrition Journal, doi: 10.1186/1475-2891-14-6

[30] Shahjehan, R D. and Bhutta, B S. (2023) "Coronary Artery Disease." Available at: https://www.ncbi.nlm.nih.gov/books/NBK56430/

[31] Shukor, M.F.A. et al. (2023) "Biomarkers for Premature Coronary Artery Disease (PCAD): A Case Control Study," Diagnostics, 13(2). Available at: https://doi.org/10.3390/diagnostics13020188.

[32] Song B, et al. (2015) "Plasma fibrinogen lever and risk of coronary heart disease among Chinese population: a systematic review and meta-analysis." Int J Clin Exp Med. 2015;8:13195–202.

[33] Sun et al. (2023), "Artificial intelligence in cardiovascular diseases: diagnostic and therapeutic perspectives." European Journal of Medical Research (2023) 28:242, https://doi.org/10.1186/s40001-023-01065-y

[34] Sun, X. et al. (2023) "Artificial intelligence in cardiovascular diseases: diagnostic and therapeutic perspectives," European Journal of Medical Research. BioMed Central Ltd. Available at: https://doi.org/10.1186/s40001-023-01065-y.

[35] Wang, X. and Zhu, H. (2024) "Artificial Intelligence in Image-based Cardiovascular Disease Analysis: A Comprehensive Survey and Future Outlook." Available at: http://arxiv.org/abs/2402.03394.

[36] World Health Organisation. (2021) 'Cardiovascular diseases (CVDs)'. Available at: https://www.googleadservices.com/pagead/aclk?sa=L&ai=DChcSEwirwfnDiZCHAxXhgVAGHWofBnYYABAAGgJkZw&ase=2&gclid=EAIaIQobChMIq8H5w4mQhwMV4YFQBh1qHwZ2EAAYASAAEgILyPD_BwE&ohost=www.google.com&cid=CAASJORo0svrZzsW-Lr3gTgAgx_5mnon7mM2RvqJmZETsLznFTYL_g&sig=AOD64_0rxGhStIVeXNTVfcOeW8XQAZUmjw&q&nis=4&adurl&ved=2ahUKEwjftPTDiZCHAxX9W0EAHURqDPcQ0Qx6BAgJEAE

[37] Zakynthinos, E. and Pappa, N. (2009) "Inflammatory biomarkers in coronary artery disease," Journal of Cardiology, pp. 317–333. Available at: https://doi.org/10.1016/j.jjcc.2008.12.007.

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Christopher is enthusiastic about exploring the intersection of technology and biological sciences, seeking innovative solutions to complex problems. He thrives in dynamic environments that challenge his problem-solving skills and creativity