

ORIGINAL RESEARCH ARTICLE

An explainable artificial intelligence model for an intelligent clinical support system in cardiovascular disease diagnosis

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Abstract

Cardiac magnetic resonance imaging (CMRI) enables the diagnosis of coronary artery disease (CAD) by analyzing cardiac images to detect blockages in the coronary arteries. This helps make a good diagnosis and clinical decision-making regarding further treatment. An intelligent clinical support system for CAD diagnosis was developed in this study, combining explainable artificial intelligence (XAI) with deep learning (DL). The proposed model used CMRI for diagnosis, while modified gradient-weighted class activation mapping was used for cardiac image segmentation. The segmented image, required to further simplify prediction, was then used in SHapley Additive exPlanations (SHAP) for feature selection (FS). The transformer-aided deep neural network (T-DNN) received this FS output for classification. The T-DNN learned contextual relations, thereby increasing the model's overall efficiency. The proposed model's segmentation mechanism was tested using the Dice similarity coefficient (DSC) and pixel accuracy. The DSC of the model was 0.93, indicating a strong overlap between the predicted and ground-truth segmented regions. The achieved classification accuracy of 88% surpasses that of state-of-the-art techniques. These results demonstrate that combining XAI with DL yields accurate, explainable CAD diagnosis and treatment, thereby automating and simplifying clinical trials.

Keywords: Clinical decision support; Heart disease diagnosis; Accuracy; Segmentation; Classification; Similarity index; Neurons

1. Introduction

Coronary artery disease (CAD) is a prevalent condition worldwide, characterized primarily by the blockage of the blood vessels that supply the heart muscle.¹ CAD results in problems such as angina, heart attacks, congestive heart failure, and sudden cardiac death. Early detection of CAD is crucial for reducing the risk of complications, and efficient methods are needed to assess coronary blood vessel status. Conventional diagnostics include angiography, computed tomography, and cardiac magnetic resonance imaging (CMRI), which provide comprehensive images of cardiac structures and functions noninvasively.² CMRI supports CAD diagnosis by providing detailed views of the heart wall motion and coronary arteries, revealing tissue quality. CMRI generates complex image datasets, yet clinicians encounter problems during interpretation.³ Standard image analysis tools are not efficient or accurate in handling the complex data patterns found in these images. This paved the way for better computer-aided diagnostics in CAD, enabling robust results.⁴ Diagnosing CAD using traditional methods is time-consuming due to the large volume of medical data and the subjectivity inherent in cardiologists' tests, resulting in unpredictable outcomes.⁵ Diagnostic tests that deliver results faster and with greater precision are now required, as the healthcare system (HCS) demands more rapid decision-making to better support patients. Computational methods such as machine learning (ML), deep learning (DL), and artificial intelligence (AI) hold strong potential for future use.

Computer-aided image analysis enables faster, more accurate analysis of large datasets than manual analysis.⁶ Prominent features in CMRI data, some invisible to the naked eye, can be detected once ML is trained to detect them. CAD diagnosis and prediction get automated through such a method. Human intervention is reduced, and detection is accelerated by shorter processing times. Clinical, genetic, and lifestyle data, along with patient imaging data, can also be used to measure patient status.⁷

A major change in CAD diagnosis is possible, driven by ML, DL, and AI. Diagnostic precision would improve once this technology is applied. The HCS is moving toward precision medicine, where treatment is optimized to a patient's individual features, and computational methods are increasingly important as a result.⁸ Diagnostic healthcare tests have improved to some extent since the introduction of ML and DL. Convolutional neural networks (CNNs), a type of DL, achieve good performance in diagnosing medical images, including CMRI.⁹ These models use multiple layers to recognize patterns in data. Accuracy improves across segmentation, classification, and detection alike.

Feature extraction (FE) from raw data can be guided directly by DL, which is a primary benefit for CAD diagnosis. Feature engineering is time-consuming in traditional ML, whereas DL makes this part easier to some extent. Occluded coronary arteries, myocardial infarction, and abnormal tissue patterns are among the features DL can detect from CMRI data.¹⁰ This proposed model can also identify CAD-related abnormalities, including their exact locations within the heart.

One of the main problems connected with DL is its "black-box" character. DL provides accurate results, but interpreting them is a significant challenge in clinical testing. Explainable AI (XAI) is a term coined to address this problem by increasing the interpretability of DL models. XAI explains how models make decisions by considering the significant input ranges for a given decision. Regarding CAD diagnosis, some XAI methods, such as Grad-Grad gradient-weighted class activation mapping (G-CAM), can be used to identify regions of a CMRI image that the model is focusing on, thereby supporting diagnosis.

When DL is integrated with XAI, the clinician can recognize how a particular decision was reached, thereby improving trust in AI tools and enabling their application in practice.^{11,12} A clinical decision support system (CDSS) is critical, and high-quality XAI is required in CAD diagnosis, where cardiologists and other healthcare providers need accurate, easily recognizable diagnostic data. CAD requires innovative modeling to manage common patient data, including basic details, medical history, and genetic markers. Using diverse data types and large datasets enables DL to detect patterns in CAD development and uncover potential contributing factors. Modern patient care standards include personalized treatment decisions that are important for accurate diagnosis based on each patient's unique state. DL and XAI enhance CAD diagnosis by providing faster, more precise results.

Recent developments in reliable AI suggest that explanation alone is not enough to make AI systems clinically viable. Robustness, reproducibility, external validation, uncertainty approximation, calibration, fairness across patient populations, and continuous integration into clinical workflows are other clinical requirements that reliable clinical AI systems should also meet. Modern CDSS must thus be intelligent, highly predictive, explainable, and validated to empower clinicians' trust and responsible use in healthcare settings.

2. Literature review

Diwakar *et al.*¹³ identified the best ML method for diagnosing CAD by comparing several methods. A research team studied 303 patient records, spanning

26 clinical tests, to identify the most effective model for detecting CAD early. The algorithms they tested were support vector machine (SVM), random forest (RF), and multilayer perceptron. SVM and RF outperformed other methods in this study. The highest area under the curve (AUC) and *F1*-score came from these two. The medical team's benefit was the goal of the researcher's ML design. Early CAD diagnosis and a CDSS tool were enabled by this design.

Forrest *et al.*¹⁴ developed a novel ML for cardiovascular disease (CVD) detection in patients with rheumatoid arthritis, diabetes, and hypertension, focusing on clinical biomarkers and carotid/femoral ultrasound imaging. To address class imbalance, the study employed four ML classifiers: RF, SVM, linear discriminant analysis, and the synthetic minority oversampling technique. A high accuracy of over 98% in detecting the presence of CVD was achieved, surpassing traditional CVD risk scores and providing a powerful tool for early CVD prediction in high-risk patients.

The RF classifier received the main focus in the AI model built to detect heart disease diagnosis (HDD) using ML. Healthcare data processing, logistic regression, and dataset attribute evaluation were all performed using a Python-based application developed in a previous study. The model achieved around 83% accuracy, signifying ML's ability to support HDD. The importance of reliable healthcare applications in supporting data analysis and model evaluation was emphasized by Garavand *et al.*¹⁵

Imbalanced electrocardiogram (ECG) and patient data pose a challenge, as discussed by Gul *et al.*¹⁶ A systematic literature review on using ML for HDD has been conducted. They conducted a meta-analysis of 451 research articles and acknowledged several methods for addressing data imbalance, while also highlighting the limitations of current models, particularly in interpretability and explainability. The authors recommend that future research improve the practical applicability of ML for HDD, particularly in dealing with imbalanced data.

Hassan *et al.*¹⁷ used 11 ML classifiers to predict coronary HDD and identified key features to improve prediction accuracy. Using gradient boosted trees and multilayer perceptron classifiers, high accuracy (95–96%) was achieved. Results prove that ML can be used in CDSS and as an efficient tool for HDD. In this work, the authors highlight the roles of feature selection (FS) and model performance in improving the diagnostic accuracy for coronary heart disease.

A recent study by Jindal *et al.*¹⁸ examined the integration of a deep neural network (DNN) with case-based reasoning

to diagnose CAD and assess its severity. Gaussian noise is introduced to mitigate overfitting, and the DNN achieves a high accuracy of 96.2% with an extremely low error rate. In the second phase, case-based reasoning was applied to diagnose CAD and measure its severity. This dual method provides an efficient method to improve CAD diagnosis and management simultaneously.

Kavitha *et al.*¹⁹ presented an ensemble-based ML approach for CVD prediction. The study used multiple classifiers and FE with RF to achieve a prediction accuracy of 88.70%. Ensemble models are a useful approach for combining the strengths of different algorithms to derive an accurate solution for early CVD detection, leveraging ML and DL to enhance diagnostic accuracy and CDSS.

Kehkashan *et al.*²⁰ validated an ML model to predict CAD using electronic health records. The model presented high sensitivity (94%) and specificity (82%) with an AUC of 0.95. The researchers measured a novel *in silico* CAD marker that quantified CAD risk using recognized risk factors and polygenic scores, and verified a significant improvement in clinical outcomes. This model shows promise for non-invasive CAD risk prediction and for detecting individuals who may be underdiagnosed.

Both ML and DL are applied to detect CVDs using ECG images. Transfer learning (TL) with pretrained DNNs (PDNNs), such as SqueezeNet and AlexNet, was used alongside a CNN for cardiac abnormality detection.²¹ The CNN achieved an accuracy of 98.23%, and when used as an FE, an accuracy of 99.79% was achieved using a Naïve Bayes classifier. The application of DL to ECG-based HDD validates its potential to improve ECG-based HDD

Previous studies have shown that research on ML for CVD and CAD detection has achieved significant improvements.^{22–25} The interpretability and feasibility of these models are poorly stated, and there is a research gap in improving these developments in clinical settings. Although DL methods, such as CNNs^{26–28}, achieve high accuracy in detecting abnormalities in ECG images, they are insufficiently clear for clinical approval. This could be achieved using G-CAM, which would provide visual clarification of the DL's decision.^{29,30} Such explanations can be further integrated with SHapley Additive exPlanations (SHAP) to improve interpretability by helping clinicians understand which features affect predictions. The transformer-aided DNNs (T-DNNs) are practical for FS, improving prediction accuracy by leveraging sequential medical data more efficiently and providing complete and more explainable CAD and CVD predictions.³¹

Table 1 presents an analytical synopsis of representative and formal studies, addressing AI, healthcare information

systems, magnetic resonance imaging (MRI), electronic healthcare, biomedical engineering, and intelligence-based applications for healthcare. The reviewed literature shows that different state-of-the-art AI, such as CNNs, hybrid CNN-transformer networks, graph learning, quantum DL, ResNet50, visual geometry group-19, and CNN-gated recurrent unit, are playing an increasingly important role in solving a wide range of healthcare challenges, including disease diagnosis, medical image improvement, biometric identification and recognition, clinical outcome prediction, healthcare Internet of Things security, and rehabilitation and cognitive interfaces. Many studies focus

on mobile health, virtual reality, systematic reviews, and clinical intervention methods to improve patient care, health information, and disease prevention, as well as on AI-based predictive models. While these research studies prove significant improvements in diagnostic accuracy, decision support, and healthcare delivery, many are limited by small datasets, single-center validation, or a lack of real-world deployment. Table 1 shows the rapid progress in intelligent healthcare technologies and highlights the requirement for more robust, explainable, and clinically validated AI frameworks to enable the generalization of a standardized HCS.

Table 1. Comparative summary of representative studies on AI, medical imaging, digital health, and intelligent healthcare applications

Ref.	Domain	Main objective	AI/ML technique	Data/application	Key contribution	Limitation
32	Healthcare IoT	Secure task scheduling for big data analytics	Adversarially robust scheduling	Healthcare IoT networks	Improved secure resource allocation	Limited to the scheduling environment
33	Medical imaging	Lung cancer detection	VGG-19 CNN	Lung CT/X-ray images	High-accuracy automated diagnosis	Single CNN architecture
34	Biometrics	Iris recognition at a distance	Quantum dilated CNN + attention	Iris images	Robust long-distance biometric recognition	High computational complexity
35	Image processing	Underwater image improvement	Hybrid CNN-transformer + cheetah optimization	Underwater images	Enhanced visibility and feature preservation	Dataset-specific evaluation
36	Histopathology	Automated prostate cancer grading	ResNet50 hybrid vision model	Histology images	Accurate histologic assessment	Requires large annotated datasets
37	Healthcare prediction	Liver transplantation outcome prediction	Graph embedding + counterfactual fusion	Clinical transplant data	Improved outcome prediction with explainability	Limited clinical validation
38	Women's health	Menstrual symptoms and productivity analysis	Statistical mediation analysis	Survey data	Emotional well-being mediates productivity	Observational study
39	Maternal health	Orthostatic hypotension test	Statistical analysis	Postpartum women	Identified psychosocial risk factors	Cross-sectional design
40	Sports medicine	Ankle sprain rehabilitation	Neuromuscular training	Football players	Improved pain and functional recovery	Small clinical population
41	Sports rehabilitation	Neuromuscular training with Kinesio tape	Clinical intervention	Football players	Compared to the effectiveness of taping	Short follow-up duration
42	Ophthalmology	Retinal changes in β -thalassemia	Systematic review and meta-analysis	OCT studies	Comprehensive evidence synthesis	Dependent on existing literature
43	Digital health	Mobile self-care for tuberculosis	Systematic review	Mobile health applications	Proved the effectiveness of mHealth education	Limited intervention quality
44	Herbal medicine	Turmeric extract effects	Experimental study	Laboratory model	Proved hormonal impact	Preclinical evidence
45	Nursing care	Spiritual care in the ICU	Case report	Intubated patient	Highlights holistic patient care	Single patient case

(Cont'd...)

Table 1. (Continued)

Ref.	Domain	Main objective	AI/ML technique	Data/application	Key contribution	Limitation
46	Nursing informatics	Audio-based reproductive education	Mobile application	Visually impaired adolescents	Improved health literacy accessibility	Limited usability evaluation
47	Cardiology	Heart Failure Readmission Prediction	LACE score analysis	Heart failure patients	Relationship between self-care and readmission	Single-center study
48	Maternal care	Low back pain reduction	Hypnobirthing + music therapy	Pregnant women	The combined intervention is most effective	Quasi-experimental design
49	Child nutrition	Caregiver nutrition knowledge	Statistical survey	Indonesian caregivers	Identified determinants of nutrition knowledge	Cross-sectional data
50	Pregnancy health	Mobile apps for preeclampsia	Literature review	Mobile health apps	Summarized available digital interventions	Lack of clinical trials
51	Disaster management	Disaster preparedness training	VR simulation	Community health cadres	VR improved preparedness skills	Limited geographical scope
52	Pharmacology	Green tea's anti-inflammatory effects	Experimental <i>in vivo</i> study	Mast cell model	Proven stabilizing effect of EGCG	Animal-based evidence
53	Stroke therapy	Oxygen-delivering nanobubbles	Literature review	Stroke treatment	Identified an emerging therapeutic strategy	Limited clinical evidence
54	Neurodiagnostics	Autism detection	Hybrid CNN-GRU + wavelet Optimization	EEG signals	Improved automated ASD detection	Needs external validation
55,56	BCI	Robotic control	EEG-based BCI	EEG signals	Enhanced robotic interaction using EEG	Prototype-level implementation

Abbreviations: AI: Artificial intelligence; ASD: Autism spectrum disorder; BCI: Brain-computer interface; CNN: Convolutional neural network; CT: Computed tomography; EEG: Electroencephalography; EGCG: Epigallocatechin-3-gallate; GRU: Gated recurrent unit; ICU: Intensive care unit; IoT: Internet of Things; LACE: Length of stay, acuity of admission, comorbidity, emergency department visits; ML: Machine learning; OCT: Optical coherence tomography; VGG-19: Visual geometry group-19; VR: Virtual reality.

Modern medical care and biomedical applications are being shaped by AI and personalized health care.⁵⁷ Adjunctive treatment with mebendazole and mesalamine may be of benefit in patients with ulcerative colitis. Another promising therapeutic approach for inflammatory bowel disease is drug repurposing.⁵⁸ Hosseini *et al.*⁵⁹ reviewed the literature on the use of AI for diagnosis, staging, and prognosis of NAFLD and liver fibrosis. Other researchers also reported an increasing trend in AI-powered CDSS. Zbala *et al.*⁶⁰ reported the relation between chronic migraine, photophobia, and sleep disturbances. Sleep-related factors may play a role in the pathogenesis and prognosis of migraine. Sleep was also disturbed by photophobia. Ananthakrishnan *et al.*⁶¹ applied patient-specific computational modeling simulations to optimize targeted drug delivery networks. These simulations were conducted to improve the performance of these networks. The aging of the vascular system is one of the

main factors affecting the efficiency of magnetic targeting. This was found to be the case. It also reported the first case of the association between Griscelli syndrome type 2 and systemic juvenile idiopathic arthritis, in an effort to broaden the clinical spectrum of rare immune-mediated diseases and underscore the importance of early diagnosis and multidisciplinary care.⁶²

3. Materials and methods

This section provides a summary of the research methods used in this research. The research methodology used a standard set of ML and data-preprocessing methods to enhance the reliability and interpretability of the HDD. The methods also describe the integration of new methods, including G-CAM for FS and SHAP, to improve model interpretability and provide a complete investigation of medical data for clinical applications.

3.1. Dataset description

The dataset consists of 63,648 multiparametric cardiac magnetic resonance (CMR) images, of which 26,104 are from patients diagnosed with CAD, and 37,544 are from healthy patients. The dataset is publicly available and valuable for CAD diagnostics. The patient group's diagnosis was recognized using invasive coronary angiography, the standard diagnostic practice. The images were collected using four different CMR sequences: Late gadolinium enhancement (LGE), perfusion, T2-weighted, and steady-state free precession. In each sequence, imaging was performed in the long- and short-axis planes of the heart. The long-axis views consist of 2-, 3-, and 4-chamber views, which are all made of one slice obtained from two different planes. The short-axis view comprised 10 frames reserved from the base to the top of the heart, and two frames were predicted from each position.

The four sequence types were performed for each patient, generating 13 slices per sequence and a total of 52 images per patient. A total of 1,224 patients participated in the dataset collection. Of the study participants, 722 were healthy, and 502 had CAD. The data were collected in accordance with the ethics committee of Tehran Omid Hospital, and all patients participated with informed consent. A 1.5 Tesla Magnetom Aera Siemens machine, equipped with a dedicated body coil, was used for CMR. Multiple sequences gave quantitative values for myocardial T2, native T1, and T1 map after contrast administration. Echo time from 1.06 to 3.16 ms, repetition time (TR) from 31.92 to 412.78 ms, and slice thickness of 7–8 mm are among the parameters found across diverse CMR sequences in the dataset. TrueFISP, early gadolinium enhancement, LGE, and myocardial T1/T2 sequences are included, with breath-hold times averaging 7–10 seconds.

The dataset comprises a multiparametric CMR image numbered 63,648, drawn from 1,224 patients (502 with CAD, 722 healthy). Three sets were formed from this using the alpha-thumb rule. The training set contains data from 857 patients and nearly 44,564 images. The validation set has 184 patients and nearly 9,568 images, and the testing set has 183 patients and nearly 9,516 images. Each patient has 52 multi-sequence images covering LGE, perfusion, T2-weighted, and steady-state free precession modalities across long- and short-axis views. All images from a single patient remain in the same split. An equal number of patients with and without CAD are included in each split through class-conscious sampling.

The data were partitioned only at the patient level to prevent information leakage. For each patient, all cardiac MRIs were assigned to a single subset (training or validation) for each imaging sequence and acquisition

plane. As a result, no patient contributed more than one image to any partition. This method avoids data leakage caused by highly correlated images of the same object and enables a more realistic evaluation of the model's generalization ability.

3.2. Data preprocessing

Histogram equalization is a method that adjusts an image's contrast to enhance pixel visibility. It is helpful in medical image processing, where some parts of the image may be too bright or too dark. The objective is to bring the pixel intensity values closer to an equal distribution.

Let the intensity of a pixel be $I(x, y)$ such that x and y are spatial coordinates. The cumulative distribution function (CDF) of the pixel rule is specified in **Equation 1**:

$$\text{CDF}(r_k) = \sum_{i=0}^k p(r_i) \quad (1)$$

where,

- $p(r_i)$ is the probability mass function of pixel intensities.

The output image control after histogram equalization $I'(x, y)$ is assumed in **Equation 2**:

$$I'(x, y) = \text{CDF}(I(x, y)) \times (L - 1) \quad (2)$$

where,

- L is the number of possible intensity levels.

Gaussian filtering generates less noisy images, particularly at high frequencies, which is important in medical imaging, where noise can obscure significant data. It convolves an image with a Gaussian function to reduce the pixel rule within a specified area while preserving edges. A Gaussian filter is defined in **Equation 3**:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (3)$$

where,

- σ is the Gaussian distribution's standard deviation, controlling the filter's spread.

The convolution of the image $I(x, y)$ with the Gaussian kernel $G(x, y)$ results in the denoised image $I_{\text{denoised}}(x, y)$ is stated in **Equation 4**:

$$I_{\text{denoised}}(x, y) = \sum_{i=-n}^n \sum_{j=-n}^n I(x+i, y+j) \times G(i, j) \quad (4)$$

where,

- n is the filter's window size.

Edge detection is crucial for finding edges in images.

The Sobel filter increases edges based on the gradient, which is related to features such as vessels and the edge of the myocardium in medical images. This practice is most useful for segmentation problems. The Sobel operator uses two-dimensional convolution kernels that detect horizontal and vertical edges. The kernels are assumed in Equation 5:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad (5)$$

The gradient magnitude at every point is measured as in Equation 6:

$$G(x,y) = \sqrt{(G_x * I(x,y))^2 + (G_y * I(x,y))^2} \quad (6)$$

where,

- $*$ is the convolution.
- $I(x, y)$ is the image intensity.

Based on the samples, the image shows high edge radiance. Combined, these preprocessing methods can help improve CMR image quality and, in turn, subsequent diagnostic models.

3.3. Segmentation using modified gradient-weighted class activation mapping

Segmentation was performed using modified G-CAM (MG-CAM); the subsequent stage in the model was FE. This is particularly important in tasks where medical

images are high-dimensional and key features are required, enhancing the model's performance. The MG-CAM heatmaps can delineate regions in the CMR image associated with probable CAD, while SHAP can then measure the relevance of these segmented features to the final output.

- Input representation: The input image was denoted by X , and the image was input to a CNN. The network delivered feature maps A^k at a specific intermediate convolutional layer " k " that contained spatial and semantic information. The network's last layer generated soft class scores " y_c ," similar to the model's confidence for class " c ." This configuration enabled hierarchical analysis of " X " to identify the areas that affected the target class " c ." The CNN layer $f(X; \theta)$ was specified by the learnable parameter " θ ." The segmentation method is shown in Figure 1.
- Class-specific gradients with spatial regularization: To localize the class " c ," gradients of the class score with respect to feature maps A^k were defined as g_c^k . Gradients validated the spatial position of the " i " input in A^k for predicting " c ." The spatial prior used weights $W(i, j)$ to incorporate prior data in domains via feature maps that highlight diagnostically relevant areas, such as heart structures in cardiology. For instance, $W(i, j)$ can be a Gaussian kernel that focuses on the central regions of images to improve localization.

The gradient of " y_c " for the feature maps A^k in the selected convolutional layer is computed in Equation 7:

$$g_c^k = \frac{\partial y_c}{\partial A^k} \quad (7)$$

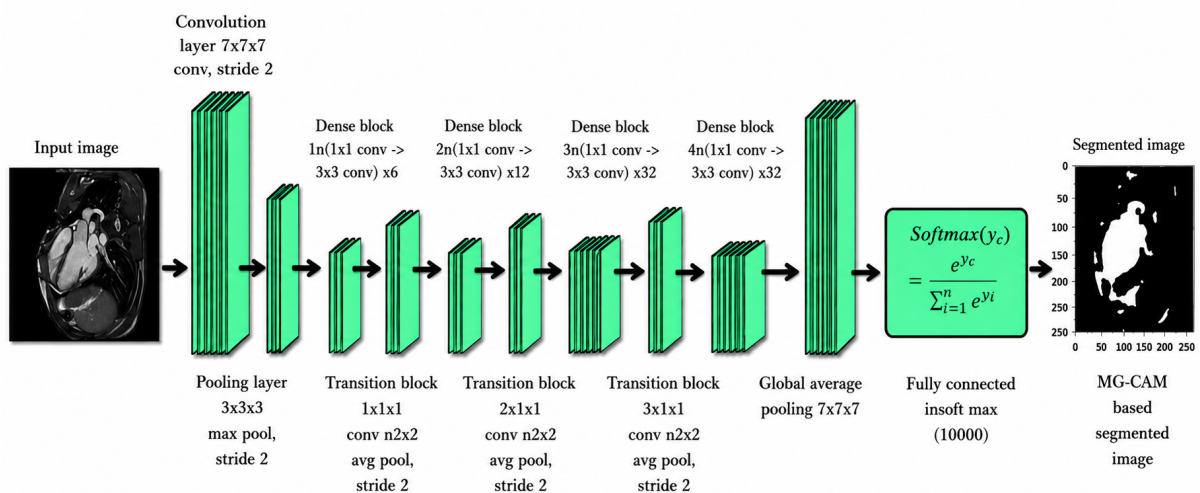


Figure 1. Proposed modified gradient-weighted class activation mapping (MG-CAM) segmentation model

Using global average pooling, a spatial regularization factor, $W(i, j)$, was applied to prioritize gradients from central or diagnostically relevant regions, as shown in **Equation 8**:

$$\alpha_c^k = \frac{\sum_{i=1}^h \sum_{j=1}^w W(i, j) \cdot g_c^k(i, j)}{\sum_{i=1}^h \sum_{j=1}^w W(i, j)} \quad (8)$$

where,

- $W(i, j)$ are the Gaussian kernels centered on diagnostically important regions or derived from prior knowledge (e.g., heart anatomy).
- (iii) Optimized weighted feature map combination: The class activation map L_c was formed from the weighted feature map. As an optimization, the proposed method did not rely solely on Good Manufacturing Practice to average over space, thereby reducing spatial detail. Instead, it employed a spatial saliency mask, $Sk(i, j)$. This mask flexibly scaled the features based on their significance for class “c.” The exclusion of negative activations eliminated noisy learning and enhanced localization accuracy by excluding all that was irrelevant to class “c.” The class activation map L_c was computed using a spatially weighted feature map specified in **Equation 9**:

$$L_c(i, j) = \text{ReLU}\left(\sum_k \alpha_c^k A^k(i, j) \cdot S_k(i, j)\right) \quad (9)$$

where,

- Positively correlated activations are measured using a rectified linear unit (ReLU), and the relevant regions are focused using a saliency mask.
- (iv) Adaptive normalization: The map was normalized to increase the readability of the activation map “ L_c ” and improve the contrast. To achieve this, “ L_c ” has been normalized with its mean “ μ_L ” and scaled by its standard deviation “ σ_L ,” thereby removing or reducing the impact of unrelated variations. A minor constant “ ϵ ” was used as a statistical constant. Adaptive normalization improved noise reduction and segmentation, as shown in **Equation 10**:

$$H_c(i, j) = \frac{L_c(i, j) - \mu_L}{\sigma_L + \epsilon} \quad (10)$$

- (v) Thresholding with optimization constraint: An optimal threshold τ_c maximizing the Dice coefficient was determined to find a binary partitioning mask M_c . This ensured the mask fit well with the ground-truth G while maintaining good recall and precision. The Dice

coefficient was ideal for medical imaging, where the correct overlap region was of particular importance. The threshold optimization method helped M_c not over-segment while capturing relevant regions. The optimization constraint is specified in **Equation 11**:

$$\tau_c = \underset{\tau}{\operatorname{argmax}} \frac{2 \cdot |M_c^\tau \cap G|}{|M_c^\tau| + |G|} \quad (11)$$

- (vi) Refinement using regularized optimization: The binary mask M_c was improved iteratively by minimizing an energy function E . In the first term, $\sum \|\nabla M_c\|^2$ muscally penalized the change in M_c across a specified point to prevent pixelated edges. The second term, $\sum |M_c - H_c|^2$, governed the optimization method by making M_c close to the normalized activation map H_c . The weights λ_1 and λ_2 brought these objectives into equilibrium, resulting in a smooth yet preserving the input heatmap. The boundary refinement was attained using **Equation 12**:

$$E(M_c) = \lambda_1 \sum_{(i,j)} \|\nabla M_c(i, j)\|^2 + \lambda_2 \sum_{(i,j)} |M_c(i, j) - H_c(i, j)|^2 \quad (12)$$

- (vii) Final optimized segmentation: The last segmentation mask M_c^* was obtained after applying the optimization method and was highlighted to correctly segment the areas most related to class “c” as specified in **Equation 13**. A smooth edge, low noise, and alignment with the G-CAM heatmap define this segmentation mask. It is particularly beneficial for tasks such as cardiac image segmentation, where accurate region identification is crucial for accurate diagnosis.

$$M_c^* = \underset{M_c}{\operatorname{argmin}} EM_c \quad (13)$$

This method refined G-CAM by integrating spatial regularization, adaptive normalization, and optimization to achieve more accurate segmentation with better visual fidelity.

The MG-CAM method can be used for segmentation, while SHAP helps identify the most important features in the segmented images, enabling a deeper understanding of the CDSS of the disease prediction models. The proposed method, SHAP, can be used in FS to assess each feature’s (region/pixel) contribution to the model output, thereby generating more XAI-driven diagnostic models. SHAP can help researchers explain each pixel’s input or region in an image when a DL model is deployed. This is particularly important in healthcare, as model-based decisions are crucial for clinicians to make informed choices. The features of MG-CAM are specified in [Table 2](#).

Table 2. Proofs of modified gradient-weighted class activation mapping

Layers	Layer details	Size of the output
Input	Input cardiac MRI image (e.g., 224×224)	224×224
Convolution	7×7 convolution, stride of 2	112×112
Pooling	3×3 max pooling, stride of 2	56×56
Dense block	1×1 convolution by 3×3 convolution $\times 6$	56×56
Transition block	1×1 convolution	56×56
	2×2 average pooling, stride of 2	28×28
Dense block	1×1 by $3 \times 3 \times 12$	28×28
Transition block	1×1 convolution	28×28
	2×2 average pooling, stride of 2	14×14
Dense block	1×1 by $3 \times 3 \times 24$	14×14
Transition block	1×1 convolution	14×14
	2×2 average pooling, stride of 2	7×7
Dense block	1×1 by $3 \times 3 \times 32$	7×7
Map FE	Gradients computed for the target class score over feature maps	7×7
Class activation map	Spatially weighted activation map for segmentation	7×7
Adaptive normalization	Normalizes the CAM using Equation 10	7×7
Thresholding	Optimal thresholding for binary segmentation mask (Equation 11)	7×7
Refinement	Regularized optimization for a smooth and accurate mask (Equation 12)	7×7
Output	Final binary segmentation mask (Equation 13)	7×7

Abbreviations: CAM: Class activation mapping; FE: Feature extraction; MRI: Magnetic resonance imaging.

However, conventional G-CAM was not developed as a segmentation algorithm, but rather, primarily as a post hoc visualization method. The proposed MG-CAM improved on the original G-CAM by adding spatial regularization, adaptive normalization, optimized threshold selection, and regularized boundary refinement. These additional optimization steps refined the coarse activation maps, producing fine segmentation masks to identify myocardial regions relevant to the diagnosis. Thus, the presented solution was an explainable localization-aided segmentation system rather than a direct U-Net-based approach.

3.4. Feature selection using SHapley Additive exPlanations

After using SHAP for FS, the SHAP values were fused into the classification model. The proposed classification involved a T-DNN. The transformer excels at establishing relationships between features across large image areas, which supports medical image analysis when the overall image context is vital. The proposed model used SHAP to identify key features for further processing. Research studies have shown that medical image segments generate key features that enhance classification performance. The FS was fed into the CNN after selection. This model employed conventional convolutions to extract local visual patterns, along with neural transformers that captured relationships between distinct image blocks. The contribution of feature “ x_i ” to the output prediction $f(x)$ was determined in **Equation 14**:

$$\phi_i(f, x) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (14)$$

where,

- The features in the SHAP value are specified as $\phi(f, x)$.
- The output for the model with a set of features is assumed to be $f(S)$.
- The set of all features is assumed to be N .

The method enabled us to identify key features for predicting CAD, allowing this study to use only those features for patient classification.

3.5. Classification on transformer-aided deep neural network

The T-DNN took the features $X_{selected} = \{x_1, x_2, \dots, x_n\}$ that SHAP selected. Each FS was converted into a more robust space to support advanced data processing. The FS was embedded into a vector space using a function $\phi: X_{selected} \rightarrow \mathbb{R}^d$. The FS “ $X_{selected}$ ” became a numeric symbol, $\mathbb{R}^d$ by the embedding transformation that used embedding dimension “ d .” The set-in features are specified in **Equation 15**:

$$X_{Embedding} = \phi(X_{Selected}) \quad (15)$$

Through FS, this study prepared input features to support transformer analysis and to disclose short- and long-range feature relationships. The T-DNN’s self-attention feature examined how the feature network, particularly in the context of medical images, revealed spatial patterns. Transformer encoders worked by first forming three matrices for each input feature—the query (Q), key (K), and value (V)—computed from attention scores. This study measured the attention connection

between features $\{x_i, x_j\}$ using **Equation 16**:

$$A_{ij} = \text{SoftMax} \left(\frac{Q_i K_j^T}{\sqrt{d_k}} \right) \quad (16)$$

where,

- A_{ij} is the attention score between features $\{x_i, x_j, dk\}$, and dk is the size of the key vector.

The self-attention mechanism computes the transformed features X' by using the attention scores to weigh the value matrix “ V ” specified in **Equation 17**:

$$X' = A \times V \quad (17)$$

where,

- A is the attention matrix, which is calculated for all pairs of features.
- V is the value matrix that contains the data required to update the FS.

After the transformer encoder processed the input features, the resulting transformed feature matrix X' was passed through a DNN for classification. The DNN consisted of multiple fully connected layers, where the final output was computed as in **Equation 18**:

$$y = f(W_{cls} \times X' + b_{cls}) \quad (18)$$

where,

- X' is the output from the T-DNN.
- W_{cls} is the weight matrix for the classification layer.
- b_{cls} is the bias term.
- $f(\cdot)$ is the activation function (e.g., Softmax or sigmoid).
- y is the predicted class, such as whether the patient has CAD (1) or not (0).

During training, the model was optimized using a cross-entropy loss function, which measured the difference between the predicted probabilities $\hat{y}_i$ and the true label “ y .” The loss function is stated in **Equation 19**:

$$L = - \sum_{i=1}^c y_i \text{Log}(\hat{y}_i) \quad (19)$$

where,

- y_i is the true label (0 or 1 for binary classification).
- $\hat{y}_i$ is the predicted probability of class i , and c is the number of classes (**Case 2**: CAD or non-CAD).

The objective was to minimize this loss function to improve CAD classification accuracy. The CAD diagnosis method is specified in [Algorithm 1](#).

The coronary disease classification method used SHAP-based FS to find key features for CAD diagnosis. The

model selected a specific set of “ X_{Selected} ” features that best help predict its output. The transformer encoder elevated the FS to a higher-dimensional space while discovering correlations in the input data via self-attention. This enabled the model to identify significant patterns in spatial measures and incorporate them to generate optimal diagnostic predictions. The enhanced features were then passed to a DNN classifier to determine CAD detection probabilities. The model learned using the cross-entropy loss function to match its predictions to the actual labels during training. The loss function enhanced model performance by optimizing the weights to minimize prediction errors, thereby improving CAD detection accuracy.

Significant progress has been made in the field of medical imaging for the automatic detection of breast cancer using ultrasound and histopathology. ML models, such as CNN and U-Net, trained with suitable hyperparameters (Adam optimizer, learning rate = 0.001, batch size = 32, dropout = 0.5, weight decay = 1×10^{-5} , and training for 50–100 epochs), have been used for tasks including lesion segmentation, malignancy classification, and subtype prediction. Researchers can achieve over 90% sensitivity and specificity when using AI to assist in diagnosing breast cancer. These AI enhancements improve radiologists’ efficiency by reducing misdiagnoses and enabling more accurate detection of abnormalities.

3.6. Implementation details

The proposed model was developed using Python (3.11, Python Software Foundation, USA) and the PyTorch DL library. Image preprocessing was performed with OpenCV, NumPy, and Scikit-image, and SHAP explanations were generated with the SHAP Python package. Model training was performed with the Adam optimizer, a learning rate of 0.001, weight decay of 1×10^{-5} , and a dropout rate of 0.5. The network was trained for 100 epochs, and the learning rate was adjusted when the validation loss stopped improving. Hyperparameter tuning was performed on the validation set to achieve the best segmentation/classification results. The transformer encoder was composed of multiple-head self-attention layers and fully connected layers for CAD classification. Experiments were performed on a workstation with an Intel Core i9 processor, 64 GB of RAM, and an NVIDIA RTX 4090 GPU (24 GB of memory), running Ubuntu 22.04. All experiments were carried out with fixed random seeds, patient-level partitioning of the datasets, identical preprocessing, and the same hyperparameter set across all experiments. These implementation details help to verify and reproduce the proposed framework independently.

Algorithm 1. for T-DNN for Classification Using SHapley Additive exPlanations-feature selection

Input	: Medical image dataset as 'X', labels as 'Y'
Output	: Classification results as $\hat{y}_i$
1. Input Representation:	
- Preprocess the medical image dataset X to generate input images. - Extract features F using SHAP to detect important regions or segments in images.	
2. FS Using SHAP:	
For each feature x_i in X, compute the SHAP value $\phi_i(f, x)$, as stated in Equation 19.	
$\phi_i(f, x) = \sum_{S \subseteq N \setminus \{i\}} \frac{ S !(N - S -1)!}{ N !} [f(S \cup \{i\}) - f(S)] \quad (19)$	
Retain features 'x_i' with high SHAP values, signifying significant help to model predictions.	
3. Transformer-Based Feature Contextualization:	
- Divide FS as F_{SHAP} into patches. - Apply the Transformer encoder to model patch dependencies, as stated in Equation 20.	
$\text{Attention}(Q, K, V) = \text{SoftMax} \left(\frac{Q_i K_j^T}{\sqrt{d_k}} \right) \quad (20)$	
Combine the Transformer outputs with the initial FS.	
4. FE Using Convolutional Layers: Passing transformer-enhanced features using convolutional layers is stated in Equation 21 .	
$F_{conv} = \text{Conv}(F_{Transformer}) \quad (21)$	
5. Classification Layer:	
- Flatten the final feature map F_{conv}. - Pass features through fully connected layers, as specified in Equation 22.	
$\hat{y}_i = \text{SoftMax}(W \cdot F_{conv} + b) \quad (22)$	
6. Model Training:	
Training the model using cross-entropy loss is specified in Equation 23.	
$L = - \sum_{i=1}^c y_i \text{Log}(\hat{y}_i) \quad (23)$	
7. Evaluation: Evaluate the model on the test set using accuracy, precision, recall, and F1-score.	
8. Output: Predict class labels $\hat{y}_i$ for new inputs.	

4. Results and discussion

This section presents the results of the proposed model, which enhances image quality through preprocessing to support accurate analysis. The MG-CAM identified specific regions in CMR images that supported CAD development. The T-DNN achieved effective CAD prediction using SHAP-based FS, as verified by the proposed classification results. This study examined the complete process, from FE image preparation and classification to CAD diagnosis accuracy confirmation. The experimental setup is specified in [Table 3](#).

Table 3. Experimental setup

Learning rate	Scalar value (e.g., 0.001, 0.01)
Optimizer	Adam: bet3a1, bet3a2, eps3ilon; SGD: momen3tum
Batch size	Integer (e.g., 32, 64, 128)
Number of training epochs	Integer (e.g., 50, 100, 200)
Regularization methods	Dropout rate (e.g., 0.2, 0.5); Weight decay coefficient (L2 penalty)

4.1. Design of preprocessing

The first phase handled data normalization in advance. The researcher applied a Gaussian filter to reduce noise and boosted contrast using histogram equalization. A consistent size was then applied to all CMR images. Irrelevant image variations were removed during this processing step. Figure 2 shows this preprocessing.

The contrast in Figure 2A was improved using histogram equalization. Gaussian filtering for noise reduction and Sobel edge detection for highlighting cardiac structures were performed. Clear separation of cardiac structures was achieved with this processing method. Figure 2B shows the processing step for Pathological CMRI. In this study, histogram equalization, Gaussian filtering, and Sobel edge detection were used, in that order, to improve image quality.

4.2. Result analysis and design of segmentation

The overlap between the predicted and actual masks was measured using the Dice similarity coefficient (DSC). This indicator shows how accurately a model locates and identifies areas of the coronary artery system, including stenosis and other abnormal features, during CAD diagnosis. The DSC score ranged from a complete mismatch (0) to a perfect match (1), indicating the degree of segmentation. True boundary and overlap capture ability were evaluated through this measurement, which examined medical image segmentation accuracy. The overlap between the ground-truth and predicted masks

was used to evaluate mask accuracy with the intersection over union (IoU) metric.

The percentage of correctly labeled pixels across the whole image is measured using pixel accuracy (PA). Overall segmentation quality was measured using the PA metric by assessing the detection of normal and abnormal coronary blood vessel regions in CAD diagnosis. PA performed well overall on the image test, but precision was lacking in small stenotic regions or plaques. Wrong-region percentage identification was used to quantify the degree of overlap between predicted and actual segmentation masks, measured as volumetric overlap error (VOE). Under- and over-segmented parts of coronary blood vessels and lesions in CMRIs were detected with the same accuracy as VOE. Segmentation quality improved as the VOE score declined. The performance was tested using Equations 24–27 (Figure 3).

$$DSC = \frac{2 \cdot |\text{Predicted} \cap \text{Ground truth}|}{|\text{Predicted}| + |\text{Ground truth}|} \quad (24)$$

$$IoU = \frac{|\text{Predicted} \cap \text{Ground truth}|}{|\text{Predicted} \cup \text{Ground truth}|} \quad (25)$$

$$PA = \frac{\text{Number of correctly labeled pixels}}{\text{Total number of pixels}} \quad (26)$$

$$VOE = 1 - IoU \quad (27)$$

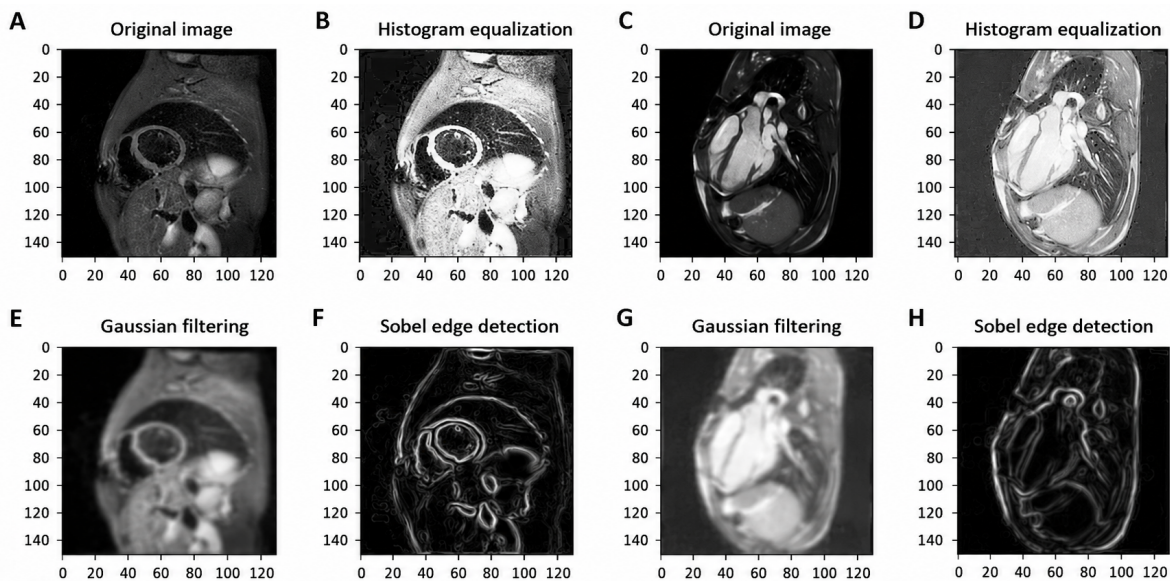


Figure 2. Preprocessing of cardiac magnetic resonance imaging CMRI. (A) Normal CMRI. (B) Pathological CMRI

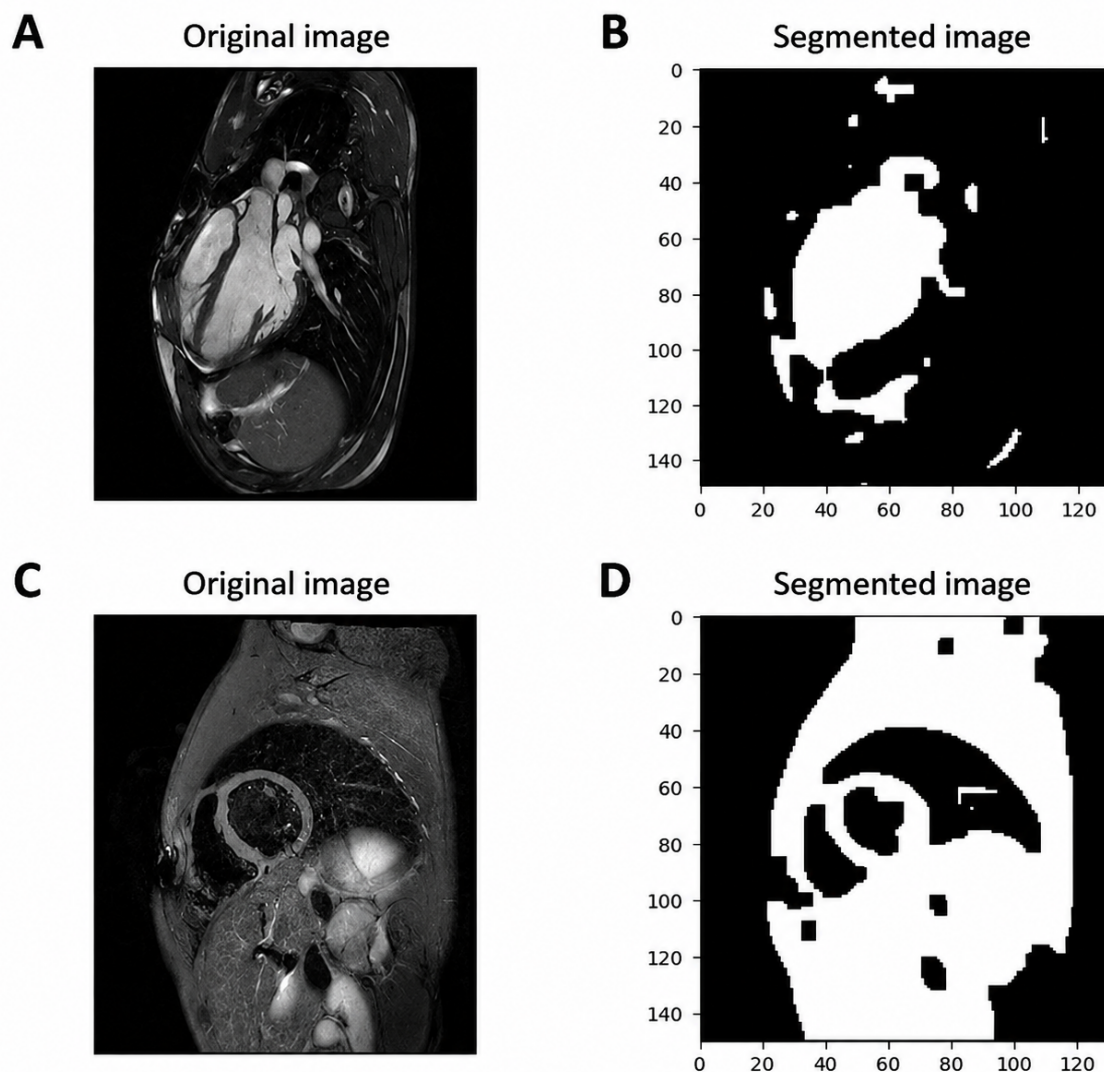


Figure 3. Segmented (A) normal and (B) sick images

Figure 4A proves how the MG-CAM performed segmentation better than DNN and TL models that use a pre-trained DNN. The proposed model excelled at mask segmentation, as shown by the DSC metric, which measured the precise overlap between predicted and actual masks. The MG-CAM achieved higher spatial accuracy for coronary artery features, as indicated by the IoU metric in Figure 4B. The PA graph in Figure 4C shows that the model accurately identified and segmented normal and abnormal pixel regions. The proposed method exhibited the lowest error rates (Figure 4D) according to the VOE metric, effectively addressing over- and under-segmentation. The MG-CAM was more efficient than traditional methods at accurately detecting and segmenting medical images.

4.3. Outcome analysis and design of classification

Accuracy was used to evaluate the CAD diagnostic model's correctness. The accuracy metric provided an overall performance view, but it lost its usefulness when the dataset contained more normal than disease samples. High accuracy rates did not guarantee effective detection of critical coronary stenosis or significant luminal narrowing associated with CAD. The Matthews correlation coefficient (MCC) evaluates the quality of binary classification by combining true positives, true negatives, false positives, and false negatives into a single unified score. Prediction accuracy is shown by a score ranging from a completely incorrect answer (−1) to an exact match (1), with 0 meaning no better than a random guess. CAD and healthy

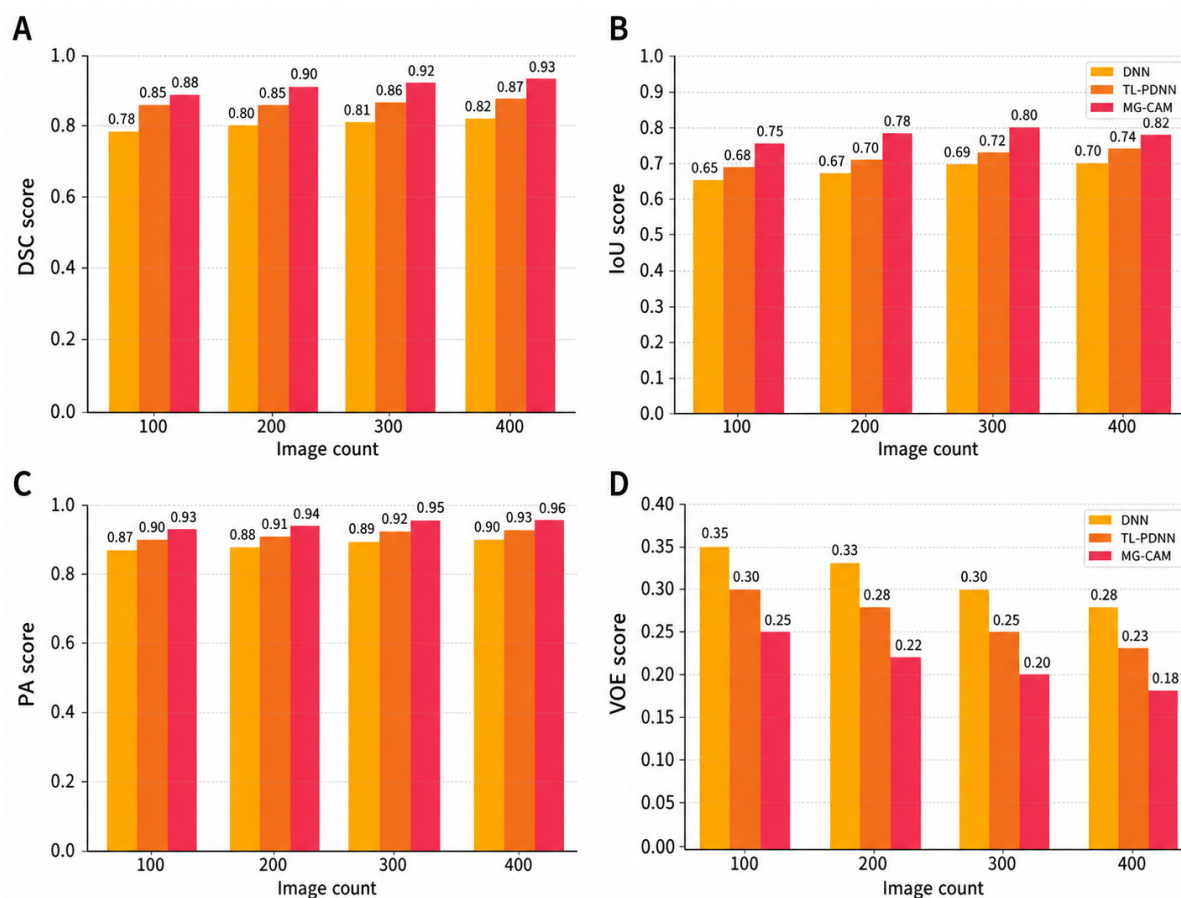


Figure 4. Comparison of segmentation performance. (A) Dice similarity coefficient. (B) Intersection over union. (C) Pixel accuracy. (D) Volumetric overlap error.

prediction were measured fairly through MCC, even when the dataset remained imbalanced, and this metric performed well for CAD diagnosis. **Equations 24 and 25** were used to assess performance.

Figure 5 shows that the proposed T-DNN combines DL and transformative methods to improve the recognition of vital data elements. T-DNN outperforms CNN + DNN, particularly on challenging datasets, by improving classification performance.

4.4. Discussion

Deep neural network, TL-PDNN, MG-CAM, ensemble-based ML, CNN, and T-DNN were among the models that received a complete performance analysis on the data for segmentation and classification tasks. DSC, IoU, PA, and VOE were evaluated as performance metrics for the segmentation task across image counts of 100, 200, 300, and 400. All metrics showed that MG-CAM consistently

outperformed other models. The DSC value for MG-CAM ranged from 0.88 for 100 images to 0.93 for 400 images. For IoU, MG-CAM reached 0.82 at 400 images, outperforming TL-PDNN and DNN. For PA, MG-CAM reached 0.96 at 400 images, above TL-PDNN (0.93) and DNN (0.9). VOE value for MG-CAM started at 0.25 for 100 images and dropped to 0.18 for 400 images, the lowest among the models.

Accuracy and MCC were used to evaluate performance in a classification task, both evaluated on the same set of images. T-DNN achieved the best performance on both metrics, with accuracies of 0.85 at 100 images and 0.88 at 400 images. CNNs and DNNs also demonstrated viable performance, although T-DNNs remained superior. For MCC, T-DNN achieved the highest value, achieving 0.76 at 100 images and 0.79 at 400 images. Ensemble-based ML and CNNs followed closely behind, but T-DNN consistently outperformed other models. G-CAM performed well in

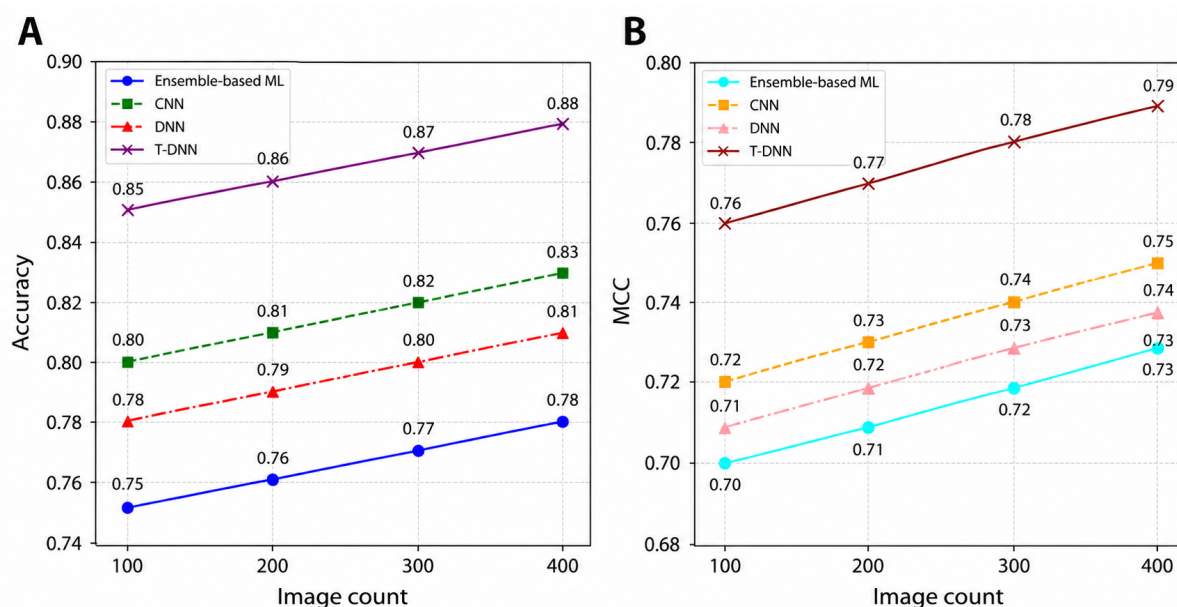


Figure 5. Comparison of classification performance. (A) Accuracy comparison. (B) MCC comparison.

Abbreviations: CNN: Convolutional neural network; DNN: Deep neural network; MCC: Matthews correlation coefficient; ML: Machine learning; T-DNN: Transformer-aided deep neural network.

the segmentation task, whereas T-DNN performed well in the classification task.

The proposed model combined MG-CAM and SHAP to enhance transparency by providing spatial and feature-level explanations. While MG-CAM identifies regions of the image that are important for predicting CAD, SHAP measures how each image feature contributes to the final classification. These visualization methods make the results more interpretable, but expert cardiologists have not measured the results, and they do not include quantitative localization measures (such as pointing-game accuracy or IoU between explanation maps and manually annotated pathological areas). Thus, the explainability results should be seen as qualitative evidence to improve the model's transparency, but not as clinical evidence. Future studies should include a quantitative assessment and analysis of the quality of cardiologists' explanations to further validate their clinical usefulness.

Other clinical evaluation metrics, such as sensitivity, specificity, precision, *F1*-score, receiver operating characteristic analysis, AUC, and precision-recall curves, should be used to comprehensively assess diagnostic performance, in addition to overall classification accuracy. The metrics provide a balanced measure of classifier behavior, especially in cases of imbalanced class distributions. Calibration analysis and decision-curve

analysis should be added to future versions of the model for measuring the reliability and clinical utility of predicted probabilities.

It should be noted that these results were obtained on a single publicly available cardiac MRI dataset. As imaging protocols, scanner vendors, and patient populations vary across clinical sites, the generalizability of the proposed model to data acquired from different scanners or clinical centers has not yet been verified and remains an important direction for external validation.

It is important to distinguish between explainability, i.e., the ability to visualize which regions or features influenced the model's output, and clinical interpretability, i.e., whether these explanations align with and are actionable within established clinical reasoning. Signifying the former does not by itself establish the latter, which requires structured evaluation by domain experts.

4.5. Ablation study

The importance of each component in the proposed model was quantified by progressively removing or replacing each module while maintaining the training and evaluation conditions. We tested four variants of the model: (i) the base T-DNN without the MG-CAM module, (ii) the base T-DNN without SHAP-based FS, (iii) a CNN model that has a transformer encoder module replaced by a CNN

module while keeping the rest of the model, and (iv) the complete proposed model. Comparisons showed that each component performed a task that contributed to diagnostic performance in this experiment. Removing MG-CAM reduced localization quality because diagnostically relevant regions were insufficiently highlighted prior to FE. Removing SHAP-based FS resulted in redundant features, thereby reducing classification performance. Likewise, the transformer model's capacity to learn long-range relationships between cardiac MR images was lost when it was replaced with a classic CNN. The proposed model achieved the best segmentation and classification results, and it is evident that the projected improvements are due to the balancing effects of all components, not simply to the number of components.

5. Conclusion

The intelligent clinical support system (ICSS) achieves precise CAD diagnosis through XAI and DL, thereby enhancing diagnostic accuracy and interpretability. Applying MG-CAM to CMRI scans, the system marks important CAD features using accurate image segmentation. We applied SHAP to analyze segmented data, enabling us to discover and prioritize key features that support accurate predictions. The clear explanations help clinicians recognize why the model generates specific predictions, thereby increasing trust in its diagnostic decisions. The T-DNN analyzes patient data to predict diagnoses by understanding the interrelationships among multiple data elements. The model achieved 88% diagnostic accuracy and a DSC of 0.93 in segmentation. This is an outstanding performance, indicating the method's efficiency and utility. XAI is integrated into classification to handle DL's black-box problem. Reliable results and a clear explanation both come from this. Better-informed CAD decisions and treatment plans become possible for clinicians through new developments in ICSS. The system also promotes the use of OpenAI in a medical setting.

Building a larger dataset that covers diverse population groups depends heavily on researchers and on adding clinical data and genetic markers to make the model work better for all individuals. Collaboration across the medical sector for training, while maintaining patient data privacy, will become possible through future research in federated learning. ICSS will provide more personalized HCS services through these new capabilities, enabling faster treatment responses and improved patient outcomes for individuals with CAD.

Despite the promising experimental results, several limitations remain. First, the proposed model was tested on a single publicly available cardiac MRI dataset and might

not capture all the imaging variability across hospitals and scanners from different vendors. Second, external validation using independent multicenter data has not yet been performed. Third, the explainability aspect has been tested qualitatively without the involvement of expert clinicians. Lastly, clinical validation is required to make the model ready for clinical use in cardiovascular CDSS. These limitations should be addressed in future work via multicenter validation, clinician-based explanation validation, uncertainty estimation, validation analysis, and prospective clinical evaluation. The proposed model should be measured as an assisting CDSS rather than a standalone diagnostic system. The explainable visualization, created using MG-CAM, and the feature importance analysis from SHAP can help clinicians understand the model's reasoning when making CAD assessments. However, clinical use should remain at the discretion of the expert and be based on the patient's history, laboratory, and imaging results until large-scale, prospective clinical studies are performed and published.

Future studies should also use repeated cross-validation to evaluate the reliability of experimental improvements in performance and will employ statistical hypothesis testing, such as paired *t*-tests or Wilcoxon signed-rank tests, as applicable. Major performance measures should also be reported with confidence intervals to assess whether experimental improvements over competing methods are due to sampling variability or a true improvement.

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Conflict of interest

The authors declare they have no competing interests.

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Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

The dataset used in this study is publicly available through the Kaggle repository (<https://www.kaggle.com/datasets/anhoangvo/acdc-dataset>). The Automated Cardiac Diagnosis Challenge (ACDC) dataset can be accessed at the Kaggle ACDC Dataset. The dataset was used for research and experimental evaluation in accordance with the terms and conditions of the data provider.

Availability of code

The source code and implementation associated with this study are publicly available through GitHub at <https://github.com/sudhakarsengan/cardiovascular-disease-diagnosis>. The repository contains the implementation notebooks, source code, dependency specifications, and supporting files required to reproduce the proposed cardiovascular disease diagnosis pipeline.

For long-term archival and reproducibility, the associated computational artifact has also been deposited in Zenodo and is available at Zenodo: doi:10.5281/zenodo.21846788. The archived release includes the CAD_MRI_Diagnosis_1 (1).ipynb implementation and is assigned DOI 10.5281/zenodo.21846788.

The clinical dataset used in the study is not publicly redistributed because it comprises restricted clinical data. Therefore, the repository provides the computational implementation and a reproducible synthetic-data execution pathway, while the original clinical data remain subject to the applicable institutional and data-access restrictions.

References

1. Abdul Raheem AK, Dhannoon BN. A novel deep learning model for drug-drug interactions. *Curr Comput Aided Drug Des.* 2024;20(5):666-672.
doi: 10.2174/0115734099265663230926064638
2. Ahsan MM, Siddique Z. Machine learning-based heart disease diagnosis: a systematic literature review. *Artif Intell Med.* 2022;128:102289.
doi: 10.1016/j.artmed.2022.102289
3. Hashim W, Thabit R, Al Barazanchi II, *et al.* Optimizing the clinical decision support system (CDSS) by using recurrent neural network (RNN) language models for real-time medical query processing. *Comput Mater Contin.* 2024;81(3):4787-4832.
doi: 10.32604/cmc.2024.055079
4. Ali MM, Paul BK, Ahmed K, Bui FM, Quinn JM, Moni MA. Heart disease prediction using supervised machine learning algorithms: performance analysis and comparison. *Comput Biol Med.* 2021;136:104672.
doi: 10.1016/j.compbiomed.2021.104672
5. Alqahtani A, Alsubai S, Sha M, Vilcekova L, Javed T. Cardiovascular disease detection using ensemble learning. *Comput Intell Neurosci.* 2022:5267498.
doi: 10.1155/2022/5267498
6. Azmi J, Arif M, Nafis MT, Alam MA, Tanweer S, Wang G. A systematic review on machine learning approaches for cardiovascular disease prediction using medical big data. *Med Eng Phys.* 2022;105(1):103825.
doi: 10.1016/j.medengphy.2022.103825
7. Bharti R, Khamparia A, Shabaz M, *et al.* Prediction of heart disease using a combination of machine learning and deep learning. *Comput Intell Neurosci.* 2021;2021(1):8387680.
doi: 10.1155/2021/8387680
8. Bhatt CM, Patel P, Ghetia T, Mazzeo PL. Effective heart disease prediction using machine learning techniques. *Algorithms.* 2023;16(2):88.
doi: 10.3390/a16020088
9. Boukhatem C, Youssef HY, Nassif AB. Heart disease prediction using machine learning. In: *2022 IEEE International Conference on Advances in Science and Engineering Technology (ASET)*. IEEE; 2022.
doi: 10.1109/ASET53988.2022.9734880
10. Cenitta D, Arul N, Vijaya Arjunan R, Chadaga K, Andrew J. An explainable artificial intelligence framework for ischemic heart disease prediction using enhanced squirrel search feature selection. *Sci Rep.* 2026;16(1):15422.
doi: 10.1038/s41598-026-46823-0
11. Chang V, Bhavani VR, Xu AQ, Hossain MA. An artificial intelligence model for heart disease detection using machine learning algorithms. *Healthcare Anal.* 2022;2:100016.
doi: 10.1016/j.health.2022.100016
12. Sharifrazi D. CAD Cardiac MRI Dataset. Kaggle. Accessed July 6, 2026. <https://www.kaggle.com/datasets/danialsharifrazi/cad-cardiac-mri-dataset>
13. Diwakar M, Tripathi A, Joshi K, Memoria M, Singh P, Kumar N. Latest trends on heart disease prediction using machine learning and image fusion. *Mater Today Proc.* 2021;37:3213-3218.
doi: 10.1016/j.matpr.2020.09.078
14. Forrest IS, Petrazzini BO, Duffy Á, *et al.* Machine learning-

- based marker for coronary artery disease: derivation and validation in two longitudinal cohorts. *Lancet*. 2023;401(10372):215-225.
doi: 10.1016/S0140-6736(22)02079-7
15. Garavand A, Salehnasab C, Behmanesh A, *et al*. Efficient model for coronary artery disease diagnosis: a comparative study of several machine learning algorithms. *J Healthc Eng*. 2022;2022:5359540.
doi: 10.1155/2022/5359540
16. Gul G, Korejo IA, Hakro DN, *et al*. Machine Learning and Ensemble Methods for Cardiovascular Disease Prediction: A Systematic Review of Approaches, Performance Trends, and Research Challenges. *Computers*. 2026; 15(1):25.
doi: 10.3390/computers15010025
17. Hassan CAU, Iqbal J, Irfan R, *et al*. Effectively Predicting the Presence of Coronary Heart Disease Using Machine Learning Classifiers. *Sensors*. 2022; 22(19):7227.
doi: 10.3390/s22197227
18. Jindal H, Agrawal S, Khera R, Jain R, Nagrath P. Heart disease prediction using machine learning algorithms. *IOP Conf Ser Mater Sci Eng*. 2021;1022(1):012072.
doi: 10.1088/1757-899X/1022/1/012072
19. Kavitha M, Gnaneswar G, Dinesh R, Sai YR, Suraj RS. Heart Disease Prediction using Hybrid machine Learning Model. In: *2021 6th International Conference on Inventive Computation Technologies (ICICT)*. IEEE; 2021:1329-1333.
doi: 10.1109/iciet50816.2021.9358597
20. Kehkashan T, Abdelhaq M, Al-Shamayleh AS, *et al*. Sustainable and interpretable heart disease prediction: a clinical decision support approach for biomedical healthcare applications. *Sci Rep*. 2026;16(1).
doi: 10.1038/s41598-026-37840-0
21. Khawla R, Talukder MA, Layek MA, Das UK, Alazab A, Kazi M. Enhanced cardiovascular disease risk prediction using explainable machine learning and data balancing. *Discover Computing*. 2026;29:100.
doi: 10.1007/s10791-026-09973-3
22. Konstantonis G, Singh KV, Sfikakis PP, *et al*. Cardiovascular disease detection using machine learning and carotid/femoral arterial imaging frameworks in rheumatoid arthritis patients. *Rheumatol Int*. 2022;42(2):215-239.
doi: 10.1007/s00296-021-05062-4
23. Mohammed MA, Abdulkareem KH, Dinar AM, Garcia Zapirain B. Rise of deep learning clinical applications and challenges in omics data: a systematic review. *Diagnostics (Basel)*. 2023;13(4):664.
doi: 10.3390/diagnostics13040664
24. Nancy AA, Ravindran D, Raj Vincent PD, Srinivasan K, Gutierrez Reina D. IoT-cloud-based smart healthcare monitoring system for heart disease prediction via deep learning. *Electronics*. 2022;11(15):2292.
doi: 10.3390/electronics11152292
25. Nazari E, Naderi H, Tabadkani M, *et al*. Breast cancer prediction using different machine learning methods applying multi factors. *J Cancer Res Clin Oncol*. 2023;149(19):17133-17146.
doi: 10.1007/s00432-023-05388-5
26. Paul VV, Syed Masood JAI. An explainable machine learning framework for cardiovascular risk prediction using structured health data. *Front Artif Intell*. 2026;9.
doi: 10.3389/frai.2026.1812622
27. Reddy KVV, Elamvazuthi I, Aziz AA, Paramasivam S, Chua HN, Pranavanand S. Heart disease risk prediction using machine learning classifiers with attribute evaluators. *Appl Sci*. 2021;11(18):8352.
doi: 10.3390/app11188352
28. Ridha AM, Mohammed MJ, Saber HA, Chyad MH, Abdulameer MH. Advanced deep learning approaches for early detection and localization of ocular diseases. *Edelweiss Appl Sci Technol*. 2024;8(6):3708-3721.
doi: 10.55214/25768484.v8i6.2813
29. Sapra V, Sapra L, Bhardwaj A, *et al*. Integrated approach using deep neural network and case-based reasoning for detecting severity of coronary artery disease. *Alex Eng J*. 2023;68:709-720.
doi: 10.1016/j.aej.2023.01.029
30. Swathy M, Saruladha K. A comparative study of classification and prediction of cardiovascular diseases (CVD) using machine learning and deep learning techniques. *ICT Express*. 2022;8(1):109-116.
doi: 10.1016/j.icte.2021.08.021
31. ACDC Dataset. Kaggle. Accessed July 6, 2026. <https://www.kaggle.com/datasets/anhoangvo/acdc-dataset>
32. Samypen Y, Chakkaravarthy M. Adversarially robust secure scheduling algorithm for big data analytics in healthcare IoT networks. In: *International Conference on Intelligent Innovations in Engineering and Technology*. 2025.
doi: 10.1109/ICIET65921.2025.11378465
33. Rajaram R, Chakkaravarthy M, Selvam J. Cutting-edge lung cancer detection with VGG-19. In: *Lecture Notes in Networks and Systems*. Springer; 2025;1288:205-216.
doi: 10.1007/978-981-96-3102-5_15
34. Midhunchakkaravarthy D, Shirke-Deshmukh S, Deshpande V. NAS-QDCNN: neuron attention stage-by-stage quantum dilated convolutional neural network for iris recognition at a distance. *Biomed Eng Appl Basis Commun*.

- 2026;38(1):2550021.
doi: 10.4015/S1016237225500218
35. Midhunchakkaravarthy D, RangaNarayana K, Narayana VL. Underwater low-light image enhancement using a hybrid CNN-transformer framework with multi-scale feature fusion and cheetah optimization. *Discover Comput.* 2026;29:61.
doi: 10.1007/s10791-026-09925-x
36. Degadwala S, Midhunchakkaravarthy D, Khan S. Automating histologic assessment of prostate cancer with a ResNet50-based hybrid vision model. *J Trends Comput Sci Smart Technol.* 2025;7(3):295-311.
doi: 10.36548/jtcsst.2025.3.001
37. Midhunchakkaravarthy D, Kumar CK, Narayana L. Design of an improved model for liver transplantation outcome prediction using graph embedding and counterfactual fusions. In: *Proceedings of the 9th International Conference on Inventive Systems and Control.* 2025:374-382.
doi: 10.1109/ICISC65841.2025.11188077
38. Chattopadhyay D, Chandran SP, Bandyopadhyay SN. Investigating the impact of menstrual health on female productivity at work: Evidence from Malaysia. *Afr J Reprod Health.* 2025;29(12):76-86.
doi: 10.29063/ajrh2025/v29i12.8
39. Balapala KR, Chandran SP, Nyirenda NN, *et al.* Orthostatic hypotension and psychosocial adversity among postpartum women in Zambia: a cross-sectional analysis. *Clin Ter.* 2026;177(3):496-501.
doi: 10.7417/CT.2026.2034
40. Memon AG, Chandran SP, Nawaz R, Talpur RA, Memon F. Comparative effects of neuromuscular training and mobilization with movement on pain, range of motion, balance, and function in footballers with ankle sprain. *Malays J Med Health Sci.* 2025;21(5):53-61.
doi: 10.47836/mjmh.21.5.7
41. Memon AG, Chandran SP, Annosha, Zakir T, Sulaman M. Effects of neuromuscular training with and without Kinesio-tape on pain, range of motion, balance and function in footballers with ankle sprain. *J Liaquat Univ Med Health Sci.* 2025;24(1):38-44.
doi: 10.22442/jlumhs.2024.01174
42. Firdous M, Umer MF, Chandran SP. Optical coherence tomography findings in beta-thalassemia major: a systematic review and meta-analysis. *Int J Ophthalmol.* 2025;18(6):1113-1122.
doi: 10.18240/ijo.2025.06.19
43. Lismayanti L, Elengoe A, Sansuwito T, Falah M. Digital health education for tuberculosis patients: a systematic review of self-care improvement via mobile applications. *J Adv Res Des.* 2025;135(1):183-201.
doi: 10.37934/ard.135.1.183201
44. Angrainy R, Wisuda AC, Elengoe A, *et al.* The effect of 96% ethanol extract of turmeric (*Curcuma longa* L. syn. *Curcuma domestica* Val.) on estrogen hormone levels. *Healthcare Low-Resource Settings.* 2025;13(3).
doi: 10.4081/hls.2025.14021
45. Karmakar M, Panduragan SL, Said FM. A case report on meeting the spiritual need of an intubated, conscious patient. *Patient Exp J.* 2025;12(3):196-200.
doi: 10.35680/2372-0247.2042
46. Haryani H, Said FM, Nambiar N, Susilawati, Janatri S. Enhancing reproductive health literacy via audio app for visually impaired female adolescents in Indonesia: design and usability evaluation. *Malays J Nurs.* 2025;16(Suppl 2):101-108.
doi: 10.31674/mjn.2025.v16isupp2.012
47. Amalia IN, Said FBM, Nambiar N. The relationship between self-care and LACE score as the predictor of re-hospitalisation among heart failure patients in Dr. M. Salamun Hospital, Bandung, Indonesia. *Malays J Nurs.* 2025;16(3):160-169.
doi: 10.31674/mjn.2025.v16i03.016
48. Murbiah, Panduragan SL, Pardi K, Che Hassan H, Husin. Effectiveness of hypnobirthing, music therapy and combined intervention in reducing low back pain among third-trimester pregnant women: a quasi-experimental study. *F1000Research.* 2025;14:868.
doi: 10.12688/f1000research.168854.1
49. Supriatin, Dioso R, Hassan HC, Maretalinia, Supriatin MK. Determinants of caregiver's knowledge of infant's early nutrition in Indonesia. *Malays J Med Health Sci.* 2025;21(Suppl 3):105-110.
doi: 10.47836/mjmh.21.s3.16
50. Desriva N, Sansuwito TB, Dioso R. Evaluation of mobile apps for health promotion of pregnant women with preeclampsia: a literature review. *Malays J Med Health Sci.* 2025;21(Suppl 3):236-240.
doi: 10.47836/mjmh.21.s3.35
51. Calisanie NNP, Tukimin T, Dioso R, *et al.* The effect of virtual reality simulation training to improve disaster preparedness for cadre in Bandung, West Java, Indonesia. *Malays J Nurs.* 2025;16(Suppl 2):20-29.
doi: 10.31674/mjn.2025.v16isupp2.003
52. Islam MM, Azman NSN, Das SK, *et al.* Stabilizing effect of green tea extract and epigallocatechin-3-gallate (EGCG) on mast cells: an in vivo study. *Inflammopharmacology.* 2025;33(8):4685-4701.

- doi: 10.1007/s10787-025-01800-3
53. Hamzah H, Suryanti S, Ahmed IA, Semedi BP, Machin A, Hernowo AT. Review the role of oxygen-delivering nanobubbles in stroke therapy: a novel approach. *F1000Research*. 2025;14:406.
doi: 10.12688/f1000research.162742.3
54. Sarvalingam P, Vajravelu A, Bin Abdul Jamil MM, Bin Ambar R, Selvam J, Ravikumar P. A novel hybrid CNN-GRU framework with wavelet-based feature optimization for automated autism spectrum disorder detection using EEG signals. *Adv Eng Intell Syst*. 2026;5(2):243-261.
doi: 10.22034/aeis.2026.576366.1514
55. Moorthi M, Vanithalakshmi M, Hariharan N, Shyam Kumar K, Yong LC, Athithan A. EEG-based brain-computer interface for robotic application. In: *Proceedings of the 6th International Conference on Smart Electronics and Communication (ICOSEC 2025)*. 2025:574-579.
doi: 10.1109/ICOSEC67334.2025.11459790
56. Eskandari M, Alkhafaji AH-A, Al-Asady AM, *et al*. Mebendazole as an adjunct therapy with mesalamine to increase efficacy and maintenance therapy for ulcerative colitis patients: a pilot study. *Curr Pharm Des*. 2026;32(8):609-616.
doi: 10.2174/0113816128372513250616182826
57. Bakhshi A, Akbari M, Maleki F, *et al*. Artificial intelligence in non-alcoholic fatty liver disease and fibrosis: a narrative review. *Curr Pharm Des*. 2026;32.
doi: 10.2174/0113816128422676260219073220
58. Demirci S, Uludüz E, Eyüboğlu S, *et al*. Linking Photophobia, Sleep Disturbances, and Migraine Chronicity: Evidence From a Retrospective Analysis. *Brain and Behavior*. 2026;16(3).
doi: 10.1002/brb3.71311
59. Hosseini SB, Almosawy W, Takrami RK, Abdi N, Aminian S. Age-dependent efficiency of magnetic drug targeting in young and old patient-specific aortic models. *Sci Rep*. 2026;16(1):7911.
doi: 10.1038/s41598-026-39486-4
60. Zbala AF, Al Fhrnawie HS, Al Fhrnawie DS, Al-Badri SG, Khalil I. Co-occurrence of Griscelli Syndrome Type 2 and Systemic Juvenile Idiopathic Arthritis in a Pediatric Patient: A Case Report. *J Investig Med High Impact Case Rep*. 2026;14.
doi: 10.1177/23247096261428870
61. Ananthakrishnan G, Ghanimi HMA, Babu KS, *et al*. Mathematical cognitive modeling enhanced by deep learning for understanding human decision making in complex sequential tasks. *J Interdiscip Math*. 2026;29(4):1033-1044.
doi: 10.47974/JIM-2573
62. Ghanimi HMA, Akilandeswari K, Prasad HA, Sengan S, Prakash BP, Bommisetti RK. An ensemble cognitive model for stroke prediction using unstructured health information powered by machine learning. *J Mach Comput*. 2025;5(1):611-621.
doi: 10.53759/7669/jmc202505048