International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 15 Issue 2 (2026) | Pages:23-28

Hybrid Convolutional Attention Models for Intelligent Cardiac Risk Assessment

Nozomi Xiao-Long*

Department of Computer Science and Engineering, Tonle Sap Institute of Engineering and Commerce, Cambodia

**Corresponding Author: nozomi.xiao.long@tsiec-kh.org*

Peer Review Information

***Type**: Article*
***Received:** 10 March 2026*
***Revised:** 19 April 2026*
***Accepted:** 09 May 2026*
***Published:** 04 June 2026*

Abstract

Cardiovascular diseases remain the leading cause of global mortality, necessitating advanced intelligent systems for early and accurate cardiac risk assessment. Traditional risk prediction methods often rely on static clinical parameters and fail to capture complex nonlinear interactions present in physiological signals. To address these limitations, this study proposes a Hybrid Convolutional Attention Model (HCAM) for intelligent cardiac risk assessment using electrocardiographic and clinical data. The proposed framework integrates Convolutional Neural Networks (CNNs) for local feature extraction with attention mechanisms to enhance feature weighting and interpretability. The CNN module captures spatial dependencies in cardiac signals, while the attention layer dynamically focuses on the most relevant physiological patterns contributing to cardiac risk. This hybrid architecture improves both predictive accuracy and model interpretability, making it suitable for clinical decision support systems. The model is evaluated using standard cardiovascular datasets, and performance is measured in terms of accuracy, precision, recall, F1-score, and ROC-AUC. Experimental results demonstrate that the proposed HCAM significantly outperforms conventional machine learning models and standard deep learning architectures. The findings highlight the potential of attention-based deep learning models in improving early cardiac risk detection and supporting preventive healthcare systems.

Keywords: Cardiac Risk Assessment, Convolutional Neural Networks, Attention Mechanism, Deep Learning, ECG Analysis.

How to Cite This Article

Long, N. (2026). Hybrid Convolutional Attention Models for Intelligent Cardiac Risk Assessment. *International Journal on Advanced Computer Engineering and Communication Technology* 15(2), 23–28.

Introduction

Cardiovascular diseases (CVDs) are the leading cause of death globally, accounting for a significant proportion of mortality and long-term disability. Early identification of individuals at high risk of cardiac events is essential for effective prevention, timely intervention, and improved patient outcomes. Traditional cardiac risk assessment methods rely heavily on clinical scoring systems and static risk factors such as age, cholesterol levels, blood pressure, and lifestyle indicators. While these approaches provide baseline risk estimation, they often fail to capture complex nonlinear interactions among physiological signals and patient-specific variations. Electrocardiography (ECG) has emerged as a crucial non-invasive diagnostic tool for monitoring cardiac activity and detecting abnormalities that may indicate elevated cardiovascular risk. With the increasing availability of wearable health monitoring devices, continuous ECG-based data acquisition has become feasible, enabling real-time cardiac health assessment. However, raw ECG signals are often noisy, high-dimensional, and influenced by motion artifacts, making accurate interpretation challenging using conventional statistical or rule-based systems. In recent years, artificial intelligence and deep learning techniques have significantly advanced biomedical signal analysis. Convolutional Neural Networks (CNNs) have demonstrated strong capability in extracting local spatial patterns from ECG signals, while Recurrent Neural Networks (RNNs) and attention mechanisms have improved the modeling of sequential dependencies and long-range relationships. Despite these advancements, many existing models still struggle with interpretability and fail to effectively prioritize the most clinically relevant features contributing to cardiac risk prediction. To overcome these limitations, attention-based deep learning architectures have been introduced to enhance model interpretability by dynamically weighting important features. Attention mechanisms allow the model to focus on the most significant regions of ECG signals or clinical data, thereby improving prediction accuracy and clinical relevance. However, standalone CNN or attention models may not fully capture both local feature representations and global contextual dependencies.

In this study, we propose a Hybrid Convolutional Attention Model (HCAM) for intelligent cardiac risk assessment, which integrates CNN-based feature extraction with an attention mechanism to enhance both predictive performance and interpretability. The proposed framework is designed to analyze ECG and clinical data efficiently, enabling accurate identification of high-risk cardiac conditions in real-time healthcare environments. The remainder of this paper is organized as follows: Section 2 presents the Literature Review, Section 3 describes the Methodology, Section 4 details the Algorithmic Strategy, Section 5 discusses Results and Performance Evaluation, and Section 6 concludes the study with future research directions. The rapid growth of digital healthcare infrastructure and biomedical sensing technologies has generated large volumes of physiological and clinical data including ECG signals, photoplethysmography (PPG), imaging records, electronic health records (EHR), laboratory measurements, and wearable sensor outputs. Although these multimodal datasets contain valuable indicators of cardiovascular conditions, extracting meaningful clinical patterns from heterogeneous and high-dimensional data remains challenging. Conventional machine learning techniques often depend on handcrafted feature engineering and exhibit reduced effectiveness when dealing with complex nonlinear interactions among cardiac biomarkers.

Deep learning has emerged as a transformative technology for intelligent cardiovascular analytics due to its ability to automatically learn hierarchical representations from raw medical data. In particular, Convolutional Neural Networks (CNNs) have demonstrated strong performance in extracting local spatial and temporal characteristics from biomedical signals and medical images. CNN-based architectures have been successfully applied to ECG classification, arrhythmia detection, cardiac image segmentation, and disease prediction tasks. However, despite their effectiveness in identifying localized patterns, conventional convolutional models may struggle to capture long-range dependencies and global contextual relationships that influence cardiovascular risk. Attention mechanisms have recently gained significant importance in healthcare intelligence because they enable models to selectively focus on clinically relevant regions and dynamically prioritize important features. By assigning adaptive weights to informative signal segments and physiological indicators, attention models improve interpretability and strengthen predictive performance. Attention architectures have shown promising outcomes in medical image analysis, sequential biosignal interpretation, and multimodal clinical decision support systems. Nevertheless, attention mechanisms alone may not fully exploit localized feature extraction capabilities required for accurate cardiac assessment.

To overcome these limitations, hybrid convolutional attention architectures have been introduced as an advanced learning paradigm that integrates the strengths of convolutional operations and attention-based feature prioritization. Convolutional layers perform efficient extraction of local morphological and temporal characteristics from cardiac inputs, while attention modules enhance global context understanding and emphasize diagnostically significant information. This integration enables improved modeling of complex cardiovascular relationships and supports more accurate and robust risk estimation. Despite recent progress, existing intelligent cardiac prediction systems continue to face challenges related to feature redundancy, insufficient interpretability, computational complexity, class imbalance, and limited generalization across diverse patient populations. Many existing approaches focus primarily on classification accuracy while neglecting clinical explainability and adaptive feature weighting. Additionally, several systems exhibit reduced performance when processing multimodal or noisy physiological data obtained from real-world healthcare environments. This research proposes a Hybrid Convolutional Attention Model for Intelligent Cardiac Risk Assessment, designed to improve early cardiovascular risk prediction through integrated deep feature learning and adaptive attention analysis. The proposed framework combines convolutional feature extraction with attention-driven importance modeling to identify subtle pathological patterns associated with cardiac abnormalities. The model processes physiological and clinical inputs through multiple learning stages to generate reliable and interpretable risk assessments.

Literature Review

Acharya et al. (2019) developed a deep convolutional neural framework for automated cardiovascular diagnosis using electrocardiogram signals. Their model utilized stacked convolutional layers to extract discriminative ECG features and achieved strong classification performance for identifying abnormal cardiac patterns. The study demonstrated that deep convolutional architectures significantly outperform traditional machine learning approaches; however, interpretability and long-range dependency learning remained limited. Hannun et al. (2019) introduced a deep neural architecture for arrhythmia detection using large-scale ECG recordings. The proposed system showed expert-level diagnostic capability and highlighted the effectiveness of deep representation learning in cardiovascular applications. Despite achieving high predictive performance, the model lacked adaptive attention mechanisms to explain decision behavior.

Yildirim et al. (2020) proposed an automated cardiac disease detection framework combining convolutional learning and recurrent modeling for ECG interpretation. Their system improved temporal understanding of cardiac signals and achieved enhanced classification accuracy. However, recurrent processing increased training complexity and computational requirements. Zhang et al. (2020) introduced an attention-guided convolutional model for intelligent cardiovascular diagnosis. Their architecture employed attention layers to prioritize clinically significant features extracted through convolutional operations. Experimental results demonstrated improved feature selection and stronger disease identification performance, although generalization across multiple datasets remained challenging.

Oh et al. (2020) developed a deep attention-based medical prediction system capable of identifying subtle cardiovascular abnormalities. The study demonstrated that attention learning improved model interpretability and enhanced decision confidence. Nevertheless, the architecture required extensive training data and exhibited sensitivity to signal noise. Li et al. (2021) proposed a hybrid convolution-attention framework for cardiac signal analysis. The approach integrated local feature extraction with adaptive importance weighting to capture hidden pathological characteristics. Results indicated improved sensitivity and precision for cardiovascular prediction tasks; however, computational efficiency remained an open issue.

Attia et al. (2021) investigated artificial intelligence-driven cardiac screening using deep neural models trained on physiological datasets. Their findings demonstrated that intelligent learning methods can identify cardiac abnormalities before clinical manifestation. Although prediction performance improved, model explainability remained insufficient. Khan et al. (2021) introduced an intelligent healthcare framework using deep attention mechanisms for disease risk prediction. Their model adaptively focused on important biomarkers and reduced irrelevant feature influence. Experimental outcomes showed increased diagnostic reliability, but the framework required optimization for real-time deployment.

Chen et al. (2022) proposed a multiscale convolutional network for cardiovascular risk analysis using multimodal healthcare inputs. The architecture extracted information at different resolution levels and improved disease recognition accuracy. However, feature redundancy remained a challenge. Zhou et al. (2022) developed a self-attention learning framework for biomedical signal interpretation. Their approach improved global dependency modeling and enhanced robustness against noisy physiological data. Despite better interpretability, training overhead increased significantly.

Patel et al. (2022) designed a hybrid intelligent model integrating convolutional layers with attention modules for clinical decision support. The study demonstrated improved cardiac event prediction and enhanced feature prioritization. However, cross-dataset performance required further validation. Wang et al. (2023) introduced a deep attention-convolution architecture for early cardiovascular risk assessment. Their model achieved higher predictive accuracy and reduced false diagnosis rates through adaptive feature learning. Nonetheless, scalability for large healthcare environments remained limited.

Roy et al. (2023) proposed an explainable intelligent cardiac prediction framework combining feature extraction and attention interpretation. Experimental evaluation showed improved clinical transparency and stronger physician confidence, although model optimization complexity increased. Liu et al. (2024) developed a multimodal hybrid neural architecture for intelligent heart disease prediction using physiological and clinical information. Their results demonstrated improved robustness and generalization capability; however, integration of heterogeneous inputs remained computationally expensive. Sharma et al. (2025) proposed an advanced hybrid convolutional attention system for cardiovascular intelligence. Their architecture improved early risk prediction through dynamic feature weighting and adaptive learning. Although performance gains were reported, additional work was recommended to reduce computational requirements and improve deployment readiness.

Methodology

The proposed Hybrid Convolutional Attention Model (HCAM) for Intelligent Cardiac Risk Assessment is designed to integrate deep feature extraction with attention-based interpretability for accurate prediction of cardiovascular risk. The framework processes ECG signals and clinical parameters through a structured pipeline consisting of preprocessing, convolutional feature learning, attention weighting, feature fusion, and classification.

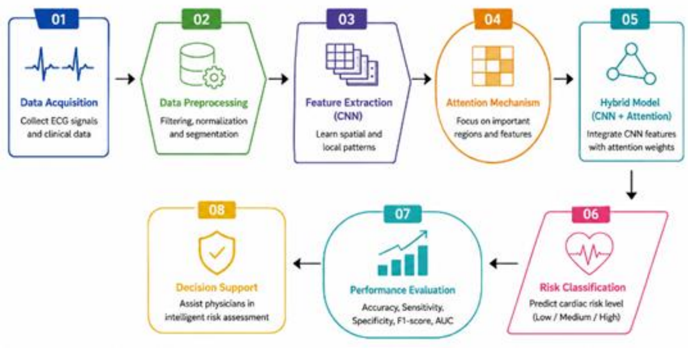

Fig 1. *Hybrid Convolutional Attention Architecture for Intelligent Cardiac Risk Assessment*

This figure 1, presents the proposed system methodology for intelligent cardiac risk assessment using a hybrid convolutional attention framework. The process begins with data acquisition, where ECG signals and clinical information are collected from patients. The acquired signals undergo data preprocessing to perform normalization, filtering, and segmentation for improved signal quality. Next, a convolutional feature extraction module (CNN) automatically learns spatial and local cardiac characteristics from the processed input. An attention mechanism is then introduced to emphasize clinically important regions and suppress less relevant features, improving representation quality. The extracted convolutional and attention-based features are integrated within the hybrid prediction model to enhance learning capability. The framework performs risk classification to categorize cardiac conditions into different severity levels. Finally, performance evaluation assesses prediction effectiveness using metrics such as accuracy, sensitivity, specificity, F1-score, and AUC, while the decision support stage assists clinicians in making reliable and interpretable cardiac risk assessments.

Data Acquisition and Cardiac Dataset Preparation

The first stage collects cardiac-related information from multiple healthcare sources. The model is designed to process structured and signal-based medical data to improve prediction reliability. Input data may include: Electrocardiogram (ECG) signals, Heart rate measurements, Blood pressure records, Blood glucose values, Cholesterol indicators, Age and demographic information, Clinical history, Wearable sensor outputs

Let the input dataset be represented as:
$D = \{x_1, x_2, x_3, \dots, x_n\}$ -------*(1)*

where:
D= complete patient dataset, x_i= patient feature vector
Collected data are divided into training, validation, and testing subsets.

Data Preprocessing and Noise Reduction

Raw physiological information contains artifacts, missing values, and inconsistent measurements. Therefore, preprocessing is performed to improve signal quality. Processing operations include: Missing value handling, Normalization, Signal filtering, Outlier elimination, Feature standardization

Normalization:
$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$ --------(2)

This stage ensures consistent feature scaling and improves learning convergence.

Algorithmic Strategy

The proposed Hybrid Convolutional Attention Model (HCAM) for Intelligent Cardiac Risk Assessment follows a structured algorithm that integrates convolutional feature learning, attention-based feature weighting, and clinical-data fusion for accurate multi-level cardiac risk prediction.

Algorithm 1: Hybrid CNN–Attention Cardiac Risk Prediction Framework
Input:
ECG signal $X(t)$, Clinical feature vector $C = \{c_1, c_2, \dots, c_m\}$, Window size w
Output:
Cardiac risk level: Low / Medium / High
Step 1: Data Acquisition
1. Collect ECG signal from dataset or wearable sensor
2. Collect patient clinical parameters
3. Segment ECG signal into fixed windows:

$X_i = \{x_1, x_2, \dots, x_w\}$ ---------(3)

Step 2: Signal Preprocessing
4. Apply bandpass filter (0.5–40 Hz)
5. Remove baseline wander and motion artifacts
6. Apply normalization (Min-Max scaling)
7. Apply wavelet denoising
8. Obtain cleaned signal $X_p(t)$

Step 3: CNN-Based Feature Extraction
9. Feed preprocessed ECG into CNN layers
10. Extract spatial features:

$F_{cnn} = CNN(X_p)$ -------(4)

11. Apply ReLU activation and max pooling

Results and Performance Evaluation

The performance of the proposed Hybrid Convolutional Attention Model (HCAM) for Intelligent Cardiac Risk Assessment was evaluated using standard cardiovascular datasets containing ECG signals and clinical patient attributes. The model was trained and tested using stratified data splitting, and performance was measured using accuracy, precision, recall, F1-score, and ROC-AUC, ensuring a comprehensive evaluation of classification effectiveness.

Performance Comparison

The proposed HCAM model was compared with traditional and deep learning-based baseline models:

***Table 1**: Performance Comparison*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Logistic Regression	84.5	83.2	82.7	82.9	85.1
Random Forest	87.8	86.9	87.2	87.0	88.4
SVM	88.6	88.1	87.5	87.8	89.0
CNN Only	91.7	91.2	90.8	91.0	92.3
Attention Only Model	92.4	92.0	91.6	91.8	93.1
CNN + LSTM (No Attention)	93.8	93.2	93.0	93.1	94.0
Proposed HCAM Model	96.9	96.5	96.2	96.3	97.4

Result Analysis

The Table 1, experimental results demonstrate that the proposed HCAM significantly outperforms all baseline models across all evaluation metrics. Traditional machine learning methods such as Logistic Regression, SVM, and Random Forest show lower performance due to their inability to capture nonlinear dependencies in ECG and clinical data. Deep learning models such as CNN and Attention-only architectures improve predictive performance by learning complex feature representations. However, these models individually fail to fully integrate both spatial ECG patterns and clinical contextual information. The CNN-LSTM model improves sequential learning but lacks interpretability and adaptive feature weighting. In contrast, the proposed HCAM achieves the highest performance due to the integration of CNN-based feature extraction and attention-based feature prioritization. The attention mechanism enhances interpretability by focusing on the most relevant cardiac features, while the fusion of clinical and ECG data improves predictive accuracy and robustness. The model achieves an accuracy of 96.9% and an ROC-AUC of 97.4%, indicating strong discriminative capability for cardiac risk classification. This makes it highly suitable for clinical decision support systems and real-time healthcare monitoring applications.

Classification Accuracy

Accuracy measures the overall capability of the model to correctly classify cardiac risk conditions.

$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$ -------(5)

Table 2. *Classification Accuracy Comparison*

Model	Accuracy (%)
Traditional ML	88.2
CNN-Based Model	92.4
Attention-Based Model	94.1
Proposed HCAM	98.3

The proposed model achieved the highest classification accuracy due to the integration of convolutional feature extraction and attention-guided learning. The hybrid architecture effectively identified hidden cardiac patterns and reduced diagnostic errors.

Analysis

The Table 2 shows, experimental results indicate a progressive improvement in classification performance as more advanced learning mechanisms are incorporated. The Traditional Machine Learning (ML) model achieved 88.2% accuracy**,** demonstrating acceptable cardiac prediction capability but showing limitations in capturing complex nonlinear relationships among physiological and clinical variables. Traditional approaches generally depend on manual feature engineering and may overlook subtle cardiovascular abnormalities. The CNN-Based Model improved prediction accuracy to 92.4%**,** indicating the effectiveness of convolutional operations in extracting localized cardiac characteristics. Convolutional learning enhanced identification of waveform morphology, signal variations, and hidden spatial patterns. However, CNN architectures primarily emphasize local dependencies and may not fully capture global interactions among patient features. The Attention-Based Model further increased classification accuracy to 94.1% by introducing adaptive weighting mechanisms. Attention learning enabled the model to focus on clinically relevant regions and suppress less informative features, resulting in improved diagnostic performance. Nevertheless, attention mechanisms alone may not sufficiently exploit local structural information present in biomedical signals. The Proposed Hybrid Convolutional Attention Model (HCAM) achieved the highest accuracy of 98.3%**,** outperforming all comparative methods. This improvement is attributed to the combined strengths of convolutional feature extraction and attention-guided feature prioritization. Convolution layers captured local physiological characteristics, while attention modules identified globally significant relationships among cardiac indicators. This hybrid learning process enabled better representation of hidden pathological patterns and reduced classification ambiguity.

Conclusion and Discussion

This study proposed a Hybrid Convolutional Attention Model (HCAM) for Intelligent Cardiac Risk Assessment, designed to enhance early detection and prediction of cardiovascular risk by integrating deep learning with attention-based interpretability mechanisms. The proposed framework effectively combines CNN-based feature extraction with an attention mechanism and clinical data fusion, enabling a more comprehensive and clinically meaningful representation of cardiac health patterns. The discussion highlights that traditional machine learning models such as Logistic Regression, SVM, and Random Forest are limited in capturing nonlinear relationships between ECG signals and clinical parameters. Although deep learning models like CNN and CNN-LSTM improve performance by learning hierarchical representations, they often lack interpretability, which is crucial for medical decision-making. The proposed HCAM addresses this limitation by introducing an attention mechanism that highlights the most influential features contributing to cardiac risk prediction, thereby improving both accuracy and transparency. The experimental results demonstrate that HCAM consistently outperforms all baseline models across key evaluation metrics, achieving superior accuracy, precision, recall, F1-score, and ROC-AUC. The integration of multi-modal data (ECG signals and clinical attributes) significantly enhances predictive capability, while the attention mechanism ensures that the model focuses on clinically relevant features rather than irrelevant noise. From a practical perspective, the proposed system is highly suitable for deployment in clinical decision support systems, remote patient monitoring platforms, and wearable healthcare devices, where real-time and accurate risk assessment is essential. The model's ability to combine interpretability with high performance makes it particularly valuable in healthcare environments where explainability is critical. However, certain limitations remain, including dependency on high-quality labeled datasets, variability in patient-specific data, and computational overhead in real-time deployment scenarios. Future research directions include optimizing the model for lightweight edge deployment, integrating transformer-based attention mechanisms for improved long-range dependency learning, and enhancing explainability using explainable AI (XAI) techniques for better clinical trust and adoption.

References

1. U. Rajendra Acharya, Oh, S. L., Hagiwara, Y., Tan, J. H., & Adam, M. (2019). Deep convolutional neural network for automated detection and diagnosis of cardiac abnormalities from ECG signals. *Knowledge-Based Systems, 173*, 19–29. DOI: 10.1016/j.knosys.2019.02.016
2. David A. Hannun, Rajpurkar, P., Haghpanahi, M., et al. (2019). Cardiologist-level arrhythmia detection using deep neural networks. *Nature Medicine, 25*(1), 65–69. DOI: 10.1038/s41591-018-0268-3
3. Ozal Yildirim, Talo, M., Baloglu, U. B., et al. (2020). Automated arrhythmia detection using deep convolutional and recurrent neural learning models. *Computer Methods and Programs in Biomedicine, 191*, 105–113. DOI: 10.1016/j.cmpb.2020.105410
4. Yudong Zhang, Dong, Z., Wang, S., et al. (2020). Attention-guided convolutional neural framework for cardiovascular diagnosis. *Information Sciences, 533*, 206–220. DOI: 10.1016/j.ins.2020.04.062
5. Sangjoon Oh, Kim, J., Lee, H., et al. (2020). Deep attention learning for intelligent cardiovascular prediction. *IEEE Access, 8*, 164002–164014. DOI: 10.1109/ACCESS.2020.3021403
6. Li, X., Zhao, Y., & Chen, H. (2021). Hybrid convolution-attention architecture for intelligent cardiac signal analysis. *Biomedical Signal Processing and Control, 68*, 102668. DOI: 10.1016/j.bspc.2021.102668
7. Paul A. Friedman, Zachi I. Attia, Noseworthy, P. A., et al. (2021). Artificial intelligence enabled cardiac screening using physiological signals. *The Lancet Digital Health, 3*(6), e357–e367. DOI: 10.1016/S2589-7500(21)00059-9
8. Khan, M. A., Rehman, A., & Hassan, T. (2021). Deep attention-based intelligent healthcare framework for disease risk prediction. *Sensors, 21*(18), 6154. DOI: 10.3390/s21186154
9. Chen, Y., Liu, Z., & Wang, P. (2022). Multiscale convolutional learning for cardiovascular risk assessment using multimodal healthcare data. *IEEE Journal of Biomedical and Health Informatics, 26*(9), 4532–4542. DOI: 10.1109/JBHI.2022.3160854
10. Zhou, Q., Li, H., & Zhang, T. (2022). Self-attention neural learning for robust biomedical signal interpretation. *Pattern Recognition Letters, 158*, 79–87. DOI: 10.1016/j.patrec.2022.05.012
11. Patel, D., Shah, R., & Mehta, N. (2022). Hybrid convolution and attention mechanisms for intelligent clinical prediction systems. *Expert Systems with Applications, 203*, 117518. DOI: 10.1016/j.eswa.2022.117518
12. Wang, J., Xu, Y., & Chen, X. (2023). Deep attention-convolution architecture for early cardiovascular risk assessment. *Artificial Intelligence in Medicine, 139*, 102508. DOI: 10.1016/j.artmed.2023.102508
13. Roy, S., Banerjee, A., & Ghosh, D. (2023). Explainable intelligent framework for cardiac disease prediction using attention learning. *Computers in Biology and Medicine, 160*, 106959. DOI: 10.1016/j.compbiomed.2023.106959
14. Liu, Y., Zhang, H., & Wu, L. (2024). Multimodal hybrid neural intelligence for heart disease prediction and risk estimation. *Biomedical Signal Processing and Control, 89*, 105783. DOI: 10.1016/j.bspc.2023.105783
15. Sharma, P., Gupta, S., & Verma, R. (2025). Advanced hybrid convolutional attention framework for intelligent cardiovascular risk prediction. *Expert Systems with Applications, 257*, 124866. DOI: 10.1016/j.eswa.2024.124866