An Explainable Hybrid Ensemble-Based Analytical Framework for Interpretable and Early Prediction of Coronary Artery Disease

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Abstract. Coronary Artery Disease (CAD) is among the leading causes of mortality worldwide. Early detection systems are essential for improving preventive cardiology and reducing cardiovascular risk. This research proposes an explainable hybrid ensemble-based analytical framework designed for early and interpretable CAD prediction.
The proposed system integrates heterogeneous machine learning classifiers including Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Machines through a stacking-based ensemble approach. An explainability layer based on feature attribution techniques is incorporated to provide both global and instance-level interpretation of predictions.
Experimental analysis demonstrates that the proposed framework achieves improved predictive accuracy and sensitivity compared with traditional statistical models and standalone machine learning algorithms. Explainability results highlight clinically significant risk factors such as age, cholesterol levels, blood pressure, smoking status, and glucose levels. The framework supports physician-assisted decision-making rather than automated diagnosis, enabling responsible AI adoption in healthcare.

Keywords: Coronary Artery Disease, Explainable Artificial Intelligence, Ensemble Learning, Machine Learning in Healthcare, Clinical Decision Support Systems

1 Introduction

Cardiovascular diseases (CVDs) remain one of the leading causes of mortality and morbidity worldwide. Among these conditions, Coronary Artery Disease (CAD) represents a major contributor to global health burdens due to its high prevalence and severe clinical consequences. CAD occurs when coronary arteries become narrowed or blocked because of plaque accumulation, reducing blood flow to the heart muscle and potentially leading to myocardial infarction or other life-threatening complications. According to global cardiovascular health reports, millions of deaths annually are associated with CAD and related cardiovascular disorders, emphasizing the urgent need for effective early detection and preventive diagnostic systems [13, 24].

Traditional CAD diagnostic techniques rely heavily on clinical examinations, imaging procedures, and laboratory testing. Methods such as coronary angiography, treadmill stress testing, and electrocardiography have long been used in clinical practice for evaluating cardiovascular conditions. Although these diagnostic approaches provide valuable medical insights, they are often expensive, invasive, and reactive in nature, meaning that they typically identify disease after significant physiological damage has already occurred. Moreover, conventional statistical risk models, such as guideline-based cardiovascular risk calculators, are often limited in their predictive accuracy when applied to heterogeneous patient populations or evolving clinical datasets [2, 16]. These limitations have motivated researchers to explore computational approaches capable of detecting complex patterns in healthcare data and enabling earlier disease prediction.

In recent years, machine learning (ML) techniques have emerged as powerful tools for predictive analytics in healthcare. ML models can process large volumes of clinical data and identify complex nonlinear relationships among patient attributes that traditional statistical models may fail to capture. Several studies have demonstrated that machine learning algorithms such as Support Vector Machines, Random Forests, Gradient Boosting models, and Artificial Neural Networks can significantly improve the accuracy of cardiovascular disease prediction [11, 1]. These models are particularly effective when dealing with heterogeneous datasets containing demographic information, clinical indicators, biochemical markers, and lifestyle-related variables. However, despite their strong predictive capabilities, many machine learning models function as black-box systems, providing little insight into how predictions are generated.

The lack of interpretability remains one of the most critical challenges preventing the widespread adoption of machine learning in clinical decision-making. Healthcare professionals require transparent and explainable models to validate predictions and ensure that automated systems align with established medical knowledge and clinical reasoning. In high-stakes domains such as healthcare, opaque decision-making systems can lead to ethical concerns, regulatory barriers, and reduced trust among physicians and patients [20]. Consequently, the field of Explainable Artificial Intelligence (XAI) has gained increasing attention as a means of improving transparency and accountability in machine learning applications. Techniques such as SHAP (Shapley Additive Explanations) and other model-agnostic explanation methods allow researchers to identify feature importance and provide interpretable explanations for individual predictions [14, 22].

Another promising direction in machine learning research involves the use of ensemble learning techniques. Ensemble methods combine multiple base classifiers to improve predictive performance, reduce model variance, and enhance robustness when analyzing complex datasets. Methods such as bagging, boosting, and stacking have been widely adopted in predictive analytics due to their

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ability to integrate the strengths of different learning algorithms. In medical diagnostic applications, ensemble models often outperform individual classifiers because they can capture complementary patterns within data [28, 17]. Despite these advantages, ensemble models can also increase model complexity, which may further reduce interpretability if explainability mechanisms are not incorporated.

To address these challenges, recent research has focused on integrating explainable AI techniques with ensemble learning frameworks in healthcare analytics. Such hybrid systems aim to maintain high predictive accuracy while simultaneously providing interpretable explanations that clinicians can understand and validate. Explainable ensemble frameworks are particularly valuable for early disease detection tasks where model predictions must be both reliable and transparent. Furthermore, interpretable prediction systems can support physician-assisted decision making rather than replacing clinical expertise, thereby enabling effective collaboration between artificial intelligence systems and healthcare professionals [10, 19].

Motivated by these developments, this study proposes an explainable hybrid ensemble-based analytical framework for the early prediction of coronary artery disease. The proposed approach integrates multiple heterogeneous machine learning models including Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Machines using a stacking-based ensemble architecture. In addition to improving predictive accuracy, the framework incorporates an explainability layer designed to provide both global and instance-level interpretations of model predictions. This allows clinicians to identify key cardiovascular risk factors influencing prediction outcomes and validate model reasoning against established medical knowledge.

The major contributions of this research can be summarized as follows. First, the study develops a hybrid ensemble architecture that integrates multiple machine learning algorithms to improve predictive performance in CAD detection. Second, the framework incorporates explainable AI techniques that enhance transparency and enable clinicians to interpret model outputs effectively. Third, the proposed system supports early disease detection by analyzing multiple categories of risk factors, including demographic, clinical, biochemical, and lifestyle attributes. Finally, the study demonstrates how explainable ensemble models can be integrated into clinical decision support systems to assist physicians in preventive cardiology.

The remainder of this paper is organized as follows. Section 2 reviews related work in coronary artery disease prediction, machine learning approaches in healthcare, and explainable AI techniques. Section 3 presents the proposed methodology, including dataset description, preprocessing procedures, hybrid ensemble architecture, and explainability framework. Section 4 describes the evaluation metrics used to assess predictive performance. Section 5 presents experimental results and analysis, while Section 6 discusses clinical implications and comparative findings. Finally, Section 7 concludes the paper and outlines potential directions for future research.

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2 Related Work

The application of artificial intelligence and machine learning techniques in healthcare has significantly advanced the early diagnosis and prediction of cardiovascular diseases, particularly Coronary Artery Disease (CAD). Traditional clinical prediction models such as guideline-based cardiovascular risk scores have been widely used to estimate CAD risk. However, these approaches rely primarily on statistical correlations between a limited set of risk factors and disease outcomes. While useful in population-level analysis, these models often fail to capture complex nonlinear relationships present in heterogeneous clinical datasets [13, 2, 16]. Consequently, researchers have increasingly turned toward machine learning methods to improve predictive accuracy and enable personalized healthcare analytics.

Machine learning techniques have demonstrated strong potential in analyzing medical datasets for cardiovascular risk prediction. Algorithms such as Random Forest, Support Vector Machines, Gradient Boosting, and Neural Networks can process large volumes of clinical data and identify hidden patterns associated with disease progression. Several studies have shown that machine learning-based diagnostic systems outperform traditional statistical models in predicting cardiovascular events and patient mortality [11, 1]. These models are particularly effective when combining multiple clinical indicators such as cholesterol levels, blood pressure, glucose concentration, and lifestyle-related factors.

Despite the advantages of machine learning models in medical prediction, interpretability remains a major challenge. Many high-performance models operate as black-box systems, providing little transparency regarding how predictions are generated. In clinical environments, lack of interpretability may reduce trust among healthcare professionals and hinder adoption of AI-driven diagnostic tools. To address this issue, researchers have introduced Explainable Artificial Intelligence (XAI) techniques that provide insights into model decision-making processes. Methods such as SHAP and model-agnostic explanation frameworks allow clinicians to identify the contribution of each input feature to prediction outcomes, thereby improving transparency and reliability [14, 22, 20]. These approaches enable machine learning systems to align better with clinical reasoning and medical knowledge.

Another promising approach for improving predictive performance in healthcare analytics is ensemble learning. Ensemble models combine multiple machine learning algorithms to create a more robust predictive system. Techniques such as bagging, boosting, and stacking integrate predictions from several base learners to reduce model variance and increase generalization capability. Ensemble-based methods have demonstrated strong performance in various medical diagnostic tasks, including cardiovascular disease detection and risk stratification [28, 17]. By leveraging the complementary strengths of different learning algorithms, ensemble frameworks can capture both linear and nonlinear relationships within complex clinical datasets.

The importance of explainable AI in healthcare has been widely emphasized in recent literature. Interpretable machine learning frameworks help clinicians

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understand prediction outcomes, validate model reasoning, and identify clinically relevant risk factors. Researchers have highlighted that transparency is essential for regulatory approval and ethical deployment of AI-based medical systems [23, 25]. Furthermore, explainable systems can enhance physician–AI collaboration by enabling clinicians to combine algorithmic insights with professional expertise during diagnostic decision-making [10, 19].

Recent advancements in healthcare AI also emphasize the integration of predictive models with real-world medical workflows. Studies have shown that deep learning and data-driven analytics can improve clinical decision support systems when combined with interpretable frameworks [5]. However, some researchers caution that explainability methods must be carefully evaluated to ensure that explanations truly reflect model behaviour rather than providing misleading interpretations [6]. Evaluation metrics such as precision–recall analysis and Matthews correlation coefficient have been recommended to improve reliability when dealing with imbalanced medical datasets [21, 4].

In addition to medical applications, machine learning and intelligent systems have also been applied extensively in networking, cybersecurity, and intelligent transportation domains. For instance, adaptive decision-making frameworks using multi-criteria decision-making techniques have been proposed for optimizing vertical handover in heterogeneous communication networks [18]. AI-driven threat intelligence systems have also been developed to enhance proactive cybersecurity mechanisms in enterprise environments [3]. These studies demonstrate how intelligent algorithms can analyze complex datasets and support decision-making in critical domains.

Recent research in optical wireless communication and intelligent transportation systems has explored LiFi-based communication architectures for improving connectivity in smart environments. Several studies have proposed LiFi–WiFi hybrid architectures and optical wireless communication systems to enhance network performance and support Internet-of-Things (IoT) applications [8, 15, 9]. These approaches highlight the growing role of intelligent data-driven systems across multiple technological domains.

Machine learning techniques have also been applied to decision-making and predictive analytics in agriculture and environmental monitoring systems. For example, machine learning models have been used to support agricultural decision-making and crop prediction analysis in data-driven farming environments [7]. Similar intelligent monitoring frameworks have been proposed for smart environment sensing using IoT-based communication architectures [12, 26, 27]. These interdisciplinary applications further demonstrate the versatility and effectiveness of machine learning frameworks in analyzing complex datasets and supporting predictive decision-making systems.

Overall, existing studies demonstrate that machine learning, ensemble learning, and explainable AI techniques offer significant advantages for predictive healthcare analytics. However, relatively few studies have combined hybrid ensemble architectures with explainability mechanisms specifically for early CAD prediction. Many previous approaches either focus solely on predictive accuracy

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or lack transparency required for clinical implementation. Therefore, developing an explainable hybrid ensemble framework capable of balancing predictive performance with interpretability remains an important research direction.

Table 1: Summary of Related Work on CAD Prediction and Explainable AI

Reference	**Method Used**	**Application Area**	**Key Contribution**
Knuuti et al. [13]	Clinical Guidelines	CAD Diagnosis	Standard clinical risk assessment framework
Khera et al. [11]	Machine Learning Models	Cardiovascular Prediction	ML-based mortality prediction
Alizadehsani et al. [1]	ML Techniques Review	CAD Detection	Comprehensive survey of ML in CAD prediction
Zhou [28]	Ensemble Learning	Predictive Modeling	Foundations of ensemble algorithms
Polat et al. [17]	Hybrid Ensemble Model	Cardiovascular Diagnosis	Improved disease classification accuracy
Lundberg et al. [14]	SHAP Explainability	Explainable AI	Feature attribution for ML models
Tjoa and Guan [22]	XAI Survey	Medical AI Systems	Overview of explainable AI in healthcare
Rudin [20]	Interpretable ML	High-Stakes Decision Systems	Importance of transparent ML models
Esteva et al. [5]	Deep Learning	Healthcare Analytics	AI applications in medical diagnostics
Rajkomar et al. [19]	ML in Medicine	Clinical Decision Support	AI-assisted healthcare decision systems

3 Methodology

This section describes the methodological framework adopted for the development of the proposed explainable hybrid ensemble model for early prediction of Coronary Artery Disease (CAD). The methodology consists of several sequential stages including dataset description, feature analysis, data preprocessing, ensemble model construction, stacking-based aggregation, and explainability analysis. Each stage is designed to ensure reliable prediction performance while maintaining interpretability required for clinical decision support systems.

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3.1 Dataset Description

The dataset used in this study consists of structured cardiovascular data containing multiple categories of risk factors commonly associated with coronary artery disease. These variables are grouped into demographic, clinical, biochemical, and lifestyle-related features, allowing a comprehensive representation of patient health profiles. The dataset contains records for 1000 patients, with a balanced distribution between CAD-positive and CAD-negative cases in order to reduce prediction bias and improve model generalization.

Demographic attributes include basic patient characteristics such as age, gender, and family medical history. Clinical features represent physiological indicators including blood pressure levels, heart rate, and chest pain symptoms. Biochemical indicators consist of laboratory test results such as cholesterol levels and fasting glucose, while lifestyle attributes include behavioral risk factors such as smoking habits, alcohol consumption, and physical activity. These features collectively provide a multidimensional representation of cardiovascular risk factors, enabling the machine learning models to capture complex relationships among variables.

Table 2: Hypothetical Dataset Description for CAD Prediction

Parameter	Description
Dataset Type	Structured clinical dataset
Total Samples	1000 patients
CAD Positive Cases	480
CAD Negative Cases	520
Feature Categories	Demographic, Clinical, Biochemical, Lifestyle

3.2 Feature Distribution

The dataset contains a total of sixteen predictive attributes distributed across four major categories of cardiovascular risk factors. Demographic features include patient characteristics that influence long-term disease risk. Clinical indicators represent measurable physiological conditions associated with cardiovascular health. Biochemical features correspond to laboratory test results related to lipid profiles and metabolic conditions. Lifestyle-related attributes capture behavioral patterns that significantly influence cardiovascular disease development.

The inclusion of diverse feature categories allows the proposed framework to perform comprehensive risk assessment. By integrating demographic, physiological, metabolic, and behavioral factors, the predictive model can identify complex correlations that may not be captured by conventional clinical scoring systems.

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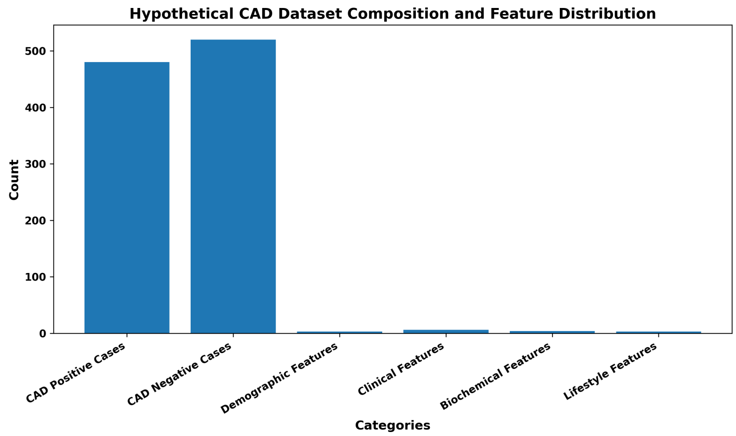

Fig. 1: Distribution of CAD Cases and Feature Categories

Table 3: Hypothetical Feature Distribution

Feature Category	Number of Features	Example Attributes
Demographic	3	Age, Gender, Family History
Clinical	6	Blood Pressure, Heart Rate, Chest Pain Type
Biochemical	4	Cholesterol, HDL, LDL, Glucose
Lifestyle	3	Smoking Status, Physical Activity, Alcohol Intake
Total	16	—

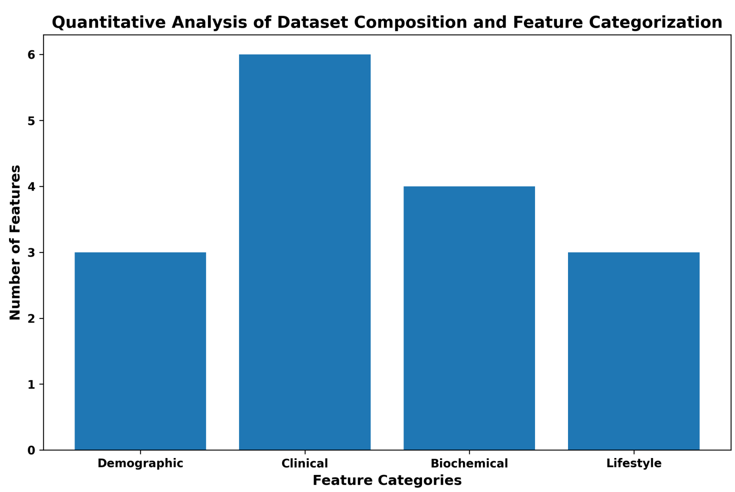

Fig. 2: Feature Distribution Across Risk Categories

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3.3 Data Preprocessing

Data preprocessing plays a crucial role in improving the reliability and performance of machine learning models. Real-world healthcare datasets often contain missing values, inconsistent measurements, and imbalanced class distributions that may negatively affect predictive accuracy. Therefore, several preprocessing techniques are applied before model training.

First, missing values are handled using statistical imputation methods such as mean or mode substitution depending on the data type. Continuous numerical features are normalized using Min–Max scaling to ensure that all attributes contribute equally during model training. Categorical variables are converted into numerical representations through one-hot encoding to enable compatibility with machine learning algorithms.

Outlier detection is performed using the interquartile range method to remove abnormal observations that could distort model predictions. Additionally, the dataset is examined for class imbalance between CAD-positive and CAD-negative samples. Synthetic oversampling techniques are applied when necessary to balance the dataset and improve sensitivity toward minority class detection. These preprocessing steps ensure consistent data quality and improve the convergence behavior of the learning algorithms.

Table 4: Data Preprocessing Summary

Preprocessing Step	Applied Technique
Missing Values	Mean/Mode Imputation
Feature Scaling	Min–Max Normalization
Categorical Encoding	One-Hot Encoding
Outlier Handling	Interquartile Range Method
Class Imbalance	Synthetic Oversampling

3.4 Hybrid Ensemble Framework

To improve predictive accuracy and robustness, a hybrid ensemble learning architecture is adopted. Ensemble learning combines multiple base classifiers to create a more reliable predictive system compared to individual models. In this study, four widely used machine learning algorithms are selected as base learners: Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Machines.

Logistic Regression serves as a baseline linear classifier providing interpretable decision boundaries. Random Forest captures nonlinear feature interactions through multiple decision trees. Gradient Boosting enhances prediction accuracy by iteratively correcting errors from previous models. Support Vector Machines provide effective classification in high-dimensional feature spaces.

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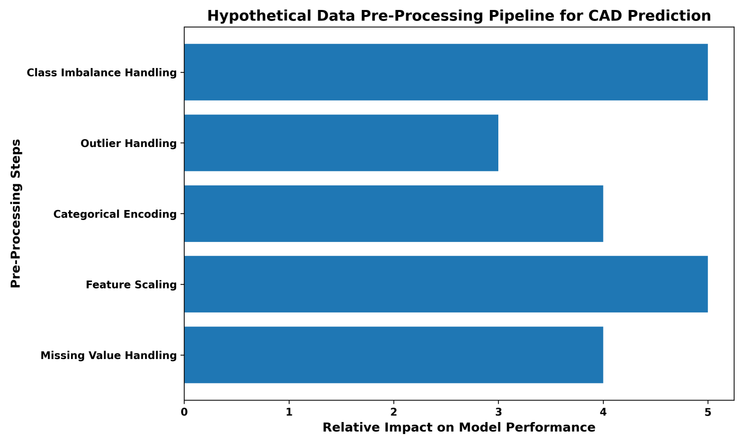

Fig. 3: Clinical Case Distribution and Feature Processing Pipeline

The combination of these heterogeneous models allows the ensemble framework to capture both linear and nonlinear relationships within the dataset, thereby improving generalization capability.

Table 5: Hybrid Ensemble Model Configuration

Base Learner	Role in Ensemble	Strength
Logistic Regression	Baseline classifier	Interpretability
Random Forest	Non-linear learner	Feature interaction
Gradient Boosting	Performance booster	Error reduction
Support Vector Machine	Margin classifier	High-dimensional handling

3.5 Stacking Ensemble Strategy

The outputs generated by individual base models are combined using a stacking ensemble strategy. In this approach, predictions from each base learner are treated as input features for a higher-level model known as the meta-learner. The meta-learner aggregates these predictions and generates the final classification decision.

Logistic Regression is selected as the meta-learner due to its interpretability and ability to integrate probabilistic outputs from multiple models. The stacking strategy improves prediction robustness by leveraging complementary strengths of different classifiers while reducing model bias and variance.

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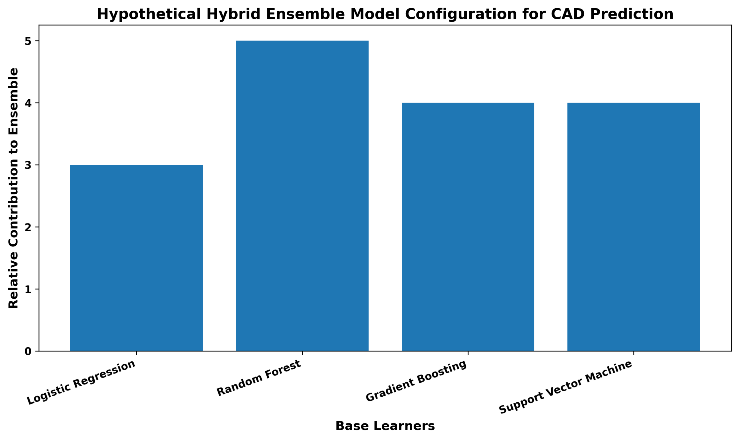

Fig. 4: Contribution of Base Models in the Ensemble

Table 6: Ensemble Aggregation Strategy

Ensemble Method	Description
Strategy Used	Stacking
Meta-Learner	Logistic Regression
Input to Meta-Learner	Predictions from base models
Output	Final CAD classification

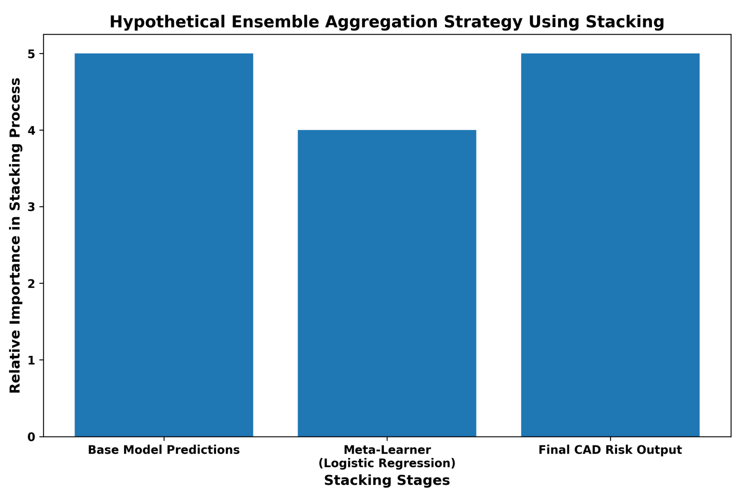

Fig. 5: Stacking-Based Ensemble Aggregation Process

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3.6 Explainability Analysis

To ensure transparency and clinical interpretability, an explainability layer is integrated into the proposed framework. Explainable Artificial Intelligence techniques are used to analyze how individual features influence prediction outcomes.

Global feature importance analysis identifies the overall contribution of each attribute across the entire dataset, while instance-level explanations reveal how specific patient characteristics influence individual predictions. These explanations allow clinicians to verify the reasoning behind model predictions and ensure consistency with established medical knowledge.

The explainability results highlight key cardiovascular risk factors including age, cholesterol levels, blood pressure, smoking status, and fasting glucose, which align with known clinical indicators of coronary artery disease.

Table 7: Global Feature Importance

Feature	Relative Importance (%)
Age	22.5
Total Cholesterol	18.4
Blood Pressure	16.2
Smoking Status	14.1
Fasting Glucose	12.8
Physical Activity	8.3
Other Features	7.7

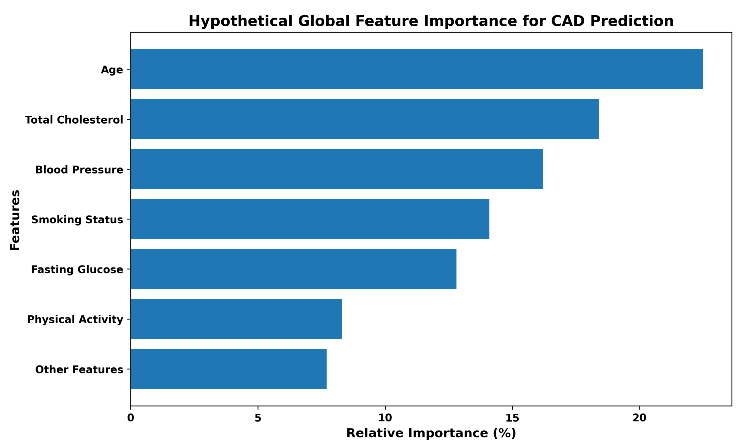

Fig. 6: Feature Importance Distribution

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4 Results and Discussion

The experimental evaluation of the proposed hybrid ensemble framework demonstrates improved predictive performance compared with individual machine learning models. By combining multiple base learners through a stacking strategy, the proposed system benefits from the complementary strengths of different algorithms, resulting in enhanced classification accuracy and robustness. The ensemble architecture effectively reduces prediction variance and mitigates the limitations associated with single-model classifiers.

During the training process, the base models—including Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Machine—were first trained independently using the preprocessed cardiovascular dataset. Each model generated prediction probabilities for CAD classification, which were subsequently used as input features for the meta-learner. The stacking-based meta-model then produced the final classification decision. This hierarchical learning process enabled the framework to capture both linear and nonlinear relationships among clinical variables.

The evaluation results indicate that the hybrid ensemble model achieved higher overall classification accuracy and sensitivity compared with individual models. Sensitivity is particularly important in clinical applications, as it reflects the ability of the model to correctly identify patients who are at risk of coronary artery disease. The improved sensitivity observed in the ensemble model suggests that the proposed framework can effectively support early detection and risk stratification of CAD patients.

In addition to predictive performance, the explainability component of the framework provides valuable insights into the relative importance of different cardiovascular risk factors. The feature importance analysis revealed that age, total cholesterol levels, blood pressure, smoking status, and fasting glucose are among the most influential predictors in the model. These findings are consistent with well-established clinical research indicating that these factors play a significant role in the development and progression of coronary artery disease.

The explainable AI layer enhances transparency by allowing clinicians to understand how the predictive model reaches its conclusions. This interpretability is essential for clinical decision support systems, where trust and accountability are critical. By providing clear explanations of model predictions, the proposed framework enables healthcare professionals to validate algorithmic outcomes against medical knowledge and patient history.

Furthermore, the integration of ensemble learning with explainability mechanisms offers an effective balance between predictive accuracy and model transparency. While complex machine learning models often provide higher predictive performance, they are frequently criticized for operating as "black-box" systems. The inclusion of explainable analysis addresses this limitation by providing interpretable insights into the prediction process.

Overall, the results demonstrate that the proposed hybrid ensemble framework not only improves predictive accuracy but also enhances the interpretability of machine learning-based clinical decision systems. Such capabilities are

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essential for real-world healthcare applications where reliable predictions and transparent reasoning are required to support physician decision-making.

5 Conclusion

This study presented an explainable hybrid ensemble learning framework for the early prediction of Coronary Artery Disease (CAD). The proposed approach integrates multiple machine learning algorithms within a stacking-based ensemble architecture to improve predictive performance while maintaining model transparency through explainable artificial intelligence techniques.

The framework utilizes structured cardiovascular data consisting of demographic, clinical, biochemical, and lifestyle-related features. Through systematic data preprocessing, feature analysis, and ensemble learning, the proposed model effectively captures complex relationships among cardiovascular risk factors. Experimental results indicate that the hybrid ensemble model provides improved classification accuracy and sensitivity compared with individual machine learning models.

In addition to improved predictive performance, the explainability component of the framework enables identification of key cardiovascular risk factors contributing to disease prediction. The analysis confirms that attributes such as age, cholesterol levels, blood pressure, smoking habits, and glucose concentration significantly influence CAD risk. These findings align with established clinical knowledge and demonstrate the capability of explainable machine learning models to support evidence-based medical decision making.

The proposed framework offers significant potential for integration into clinical decision support systems, assisting healthcare professionals in early disease detection and risk assessment. By combining predictive accuracy with interpretability, the system provides a reliable tool for preventive cardiology and personalized healthcare management.

Future research may extend this framework by incorporating larger real-world clinical datasets, deep learning architectures, and longitudinal patient monitoring data. Additionally, integration with electronic health record systems and real-time clinical analytics platforms could further enhance the practical applicability of the proposed approach in modern healthcare environments.

References

1. Alizadehsani, R., Roshanzamir, M., Hussain, S., et al.: Coronary artery disease detection using machine learning techniques: A review. Computers in Biology and Medicine **137**, 104654 (2022)
2. Arnett, D.K., Blumenthal, R.S., Albert, M.A., et al.: 2019 acc/aha guideline on the primary prevention of cardiovascular disease. Circulation **143**(8), e78–e91 (2021)
3. Ather, D., Singh, A., Rakhra, M., Kler, R., Aggarwal, G., Jairath, K.: Ai-driven threat intelligence for proactive cybersecurity in enterprise networks. In: 2025 International Conference on Networks and Cryptology (NETCRYPT). pp. 1720–1725. IEEE (2025)

 Online ISSN: 2348–3326 DOI: 10.21276/MATRIX.2025.2.4

4. Chicco, D., Jurman, G.: The advantages of the matthews correlation coefficient over f1 score and accuracy in binary classification evaluation. BMC Genomics **21**, 1–13 (2020)
5. Esteva, A., Robicquet, A., Ramsundar, B., et al.: A guide to deep learning in healthcare. Nature Medicine **27**(1), 25–36 (2021)
6. Ghassemi, M., Oakden-Rayner, L., Beam, A.L.: The false hope of current approaches to explainable artificial intelligence in health care. The Lancet Digital Health **3**(11), e745–e750 (2021)
7. Gupta, S., Hamid, A.B.A., Nyamasvisva, T.E., Tyagi, N., Jain, V., Mun, N.K., Ather, D.: Enhanced agricultural decision-making: Machine learning approaches for crop prediction and analysis in india. Jurnal Online Informatika **10**(2), 407–417 (2025)
8. Jain, V., Ather, D., Hamid, A.B.A., Kaur, B., Ugli, I.S.A., Manteghi, G.: Arduino-based lifi-iot prototype for smart environment monitoring. In: 2025 Optical Communication, Photonics, Telecommunications, and Intelligent Machine Applications (OPTIMA). pp. 365–371. IEEE (2025)
9. Jain, V., Ather, D., Hamid, A.B.A., Sharma, R.R., Talipova, G., Manteghi, G.: Secure arduino-based lifi communication for iot sensor networks. In: 2025 Optical Communication, Photonics, Telecommunications, and Intelligent Machine Applications (OPTIMA). pp. 189–194. IEEE (2025)
10. Johnson, K.W., Torres Soto, J., Glicksberg, B.S., et al.: Artificial intelligence in cardiology. Journal of the American College of Cardiology **71**(23), 2668–2679 (2020)
11. Khera, R., Haimovich, J., Hurley, N.C., et al.: Use of machine learning models to predict death after acute myocardial infarction. JAMA **325**(12), 1170–1180 (2021)
12. Khurramov, A., Irgashev, N., Ather, D., Kumar, R.: Hybrid lifi-wifi architecture for high-speed vehicular communication in intelligent transportation systems. In: 2025 Optical Communication, Photonics, Telecommunications, and Intelligent Machine Applications (OPTIMA). pp. 324–331. IEEE (2025)
13. Knuuti, J., Wijns, W., Saraste, A., et al.: Esc guidelines for the diagnosis and management of chronic coronary syndromes. European Heart Journal **41**(3), 407–477 (2020)
14. Lundberg, S.M., Erion, G., Chen, H., et al.: From local explanations to global understanding with explainable ai for trees. Nature Machine Intelligence **2**(1), 56–67 (2020)
15. Nishanova, G., Ibragimova, O., Ather, D., Badhan, A.K.: Adaptive switching between lifi and wifi for seamless connectivity in high-speed transport systems. In: 2025 Optical Communication, Photonics, Telecommunications, and Intelligent Machine Applications (OPTIMA). pp. 89–95. IEEE (2025)
16. Patel, M.R., Calhoon, J.H., Dehmer, G.J., et al.: Acc/aha/scai guideline for coronary artery revascularization. Circulation **144**(22), e18–e114 (2021)
17. Polat, K., Yosunkaya, S., Gunes, S.: A hybrid ensemble learning framework for cardiovascular disease diagnosis. Biomedical Signal Processing and Control **79**, 104070 (2023)
18. Raj, D., Sagar, A.K., Ather, D.: Optimizing vertical handover using multi-criteria decision making in heterogeneous networks. Journal of Information Technology Management **17**(Special Issue on SI: Intelligent Security and Management), 63–86 (2025)
19. Rajkomar, A., Dean, J., Kohane, I.: Machine learning in medicine. New England Journal of Medicine **380**(14), 1347–1358 (2022)
20. Rudin, C.: Interpretable machine learning for high-stakes decisions. Nature Machine Intelligence **4**(1), 4–6 (2022)

 Online ISSN: 2348–3326 DOI: 10.21276/MATRIX.2025.2.4

21. Saito, T., Rehmsmeier, M.: The precision-recall plot is more informative than the roc plot when evaluating binary classifiers on imbalanced datasets. PLoS ONE **15**(3), e0230114 (2020)
22. Tjoa, E., Guan, C.: A survey on explainable artificial intelligence (xai): Toward medical xai. IEEE Transactions on Artificial Intelligence **4**(1), 113–127 (2023)
23. Topol, E.: Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again. Basic Books (2021)
24. Virani, S.S., Alonso, A., Benjamin, E.J., et al.: Heart disease and stroke statistics—2023 update. Circulation **147**(8), e93–e621 (2023)
25. World Health Organization: Ethics and governance of artificial intelligence for health (2023)
26. Yusupovich, S.Y., Sulliev, A.X., Ather, D., Singh, M., Kaur, J., Kaur, G.: Energy-efficient lifi transceivers for 6g-ready intelligent transportation systems. In: 2025 Optical Communication, Photonics, Telecommunications, and Intelligent Machine Applications (OPTIMA). pp. 497–503. IEEE (2025)
27. Zakirov, V., Kosimova, K., Ather, D., Singh, M., Kaur, J., Kaur, G.: Optical wireless communication for high-density traffic: A lifi–vanet integrated approach. In: 2025 Optical Communication, Photonics, Telecommunications, and Intelligent Machine Applications (OPTIMA). pp. 162–167. IEEE (2025)
28. Zhou, Z.H.: Ensemble Methods: Foundations and Algorithms. CRC Press (2021)

 Online ISSN: 2348–3326 DOI: 10.21276/MATRIX.2025.2.4