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Research Article

An Improved Framework for Cardiovascular Disease Prediction using Hybrid Ensemble Learning Soft-Voting Model

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Abstract:

Cardiovascular diseases (CVDs) remain the leading cause of death globally, accounting for approximately 17.9 million deaths each year. While diagnostic technologies have advanced, traditional methods often fail to detect early-stage heart disease, particularly in asymptomatic individuals. This study presents an intelligent, interpretable machine learning framework designed to enhance early CVD prediction. guided by domain-specific medical knowledge. Two well-established datasets the Kaggle Cardiovascular Disease Dataset and the Framingham Heart Study Dataset were used for model training and evaluation. Machine learning models including Random Forest, Support Vector Machine, and neural networks were applied, along with SMOTE-Tomek Links to address class imbalance. A score-specific weighted soft voting mechanism was used to improve prediction across varying risk categories. The final model achieved high performance: Score 1 (low risk) reached 97.4% accuracy and 0.99% AUC; Score 2 (moderate risk) achieved 83.6% accuracy and 0.90% AUC; Score 3 (high risk) yielded 93% accuracy and 0.97% AUC. These results demonstrate the model's high precision, recall, and generalizability across diverse patient profiles. By combining ensemble learning, medical knowledge, and advanced risk stratification, the framework offers a clinically relevant tool for early detection and personalized intervention, supporting proactive cardiovascular healthcare.

1. Introduction

Cardiovascular diseases (CVDs) are a leading cause of global mortality, responsible for over 31% of annual deaths (WHO) [1]. Early detection is crucial, yet traditional diagnostic methods like ECG and medical imaging often fail to identify asymptomatic cases. Machine learning (ML) and deep learning (DL) have transformed CVD prediction by detecting hidden patterns in data. Algorithms such as Random Forest, Support Vector Machines (SVM), and Decision Trees have shown improved accuracy in predicting heart disease. Studies highlight the effectiveness of SVM in classification, while deep learning models like CNNs and LSTMs further enhance performance by automatically learning features from raw data. Patidar et al.,2022 showed that Random Forest can achieve an accuracy of 98.53% in predicting heart disease, making it one of the most effective algorithms for this task [2]. Similarly, (Mansoor et al.,2023) reported that LSTM models achieved 91% accuracy in predicting CVDs, further highlighting the role of deep learning in this domain [3]. The availability of large-scale datasets, such as Cleveland and Statlog, has facilitated AI-driven diagnostics. Techniques like ensemble learning and feature engineering further refine model performance. However, challenges remain in the feature. A major issue is the lack of systematic feature selection. Many models include features without assessing clinical relevance, leading to redundant or irrelevant data. Studies emphasize model accuracy but often ignore correlations between medical features, behavioral factors, and socioeconomic influences, reducing predictive reliability. Additionally, feature selection rarely integrates the latest medical research, missing opportunities for enhancement. Another limitation is the inadequate evaluation of feature impact on model performance. Strong correlations between key indicators, such as cholesterol and BMI, are often overlooked, affecting prediction reliability. Selecting features without considering their interdependence weakens model interpretability and clinical value [4]. Data imbalance further complicates CVD prediction. Many datasets are skewed toward healthy individuals, leading models to favor the majority class while underperforming in detecting high-risk cases. While techniques like SMOTE help mitigate imbalance, improper application can introduce noise or remove critical information [5]. this study proposes an intelligent framework that systematically integrates clinical knowledge, research-backed features, and data-balancing techniques. This approach aims to enhance both predictive accuracy and real-world applicability in healthcare.

2. Literature Review

2.1 Effectiveness of Various Machine Learning Algorithms for CVD Prediction

Over the past few years, numerous researchers have delved into the application of Machine Learning (ML) and Deep Learning (DL) techniques to enhance the precision of cardiovascular disease prediction. Khurana et al. explored multiple feature selection strategies, including Chi-Square and information gain, to enhance prediction accuracy [6]. They tested five distinct feature selection techniques across various algorithms, with Support Vector Machines (SVM) demonstrating superior predictive performance, attaining an accuracy of 83.41%. These findings underscore the crucial role of effective feature selection in optimizing machine learning models for CVD prediction. Mohammad et al. used hospital medical records and employed an Artificial Neural Network (ANN) model to predict heart failure admissions within one year, achieving an accuracy of 73.6% [7]. The study focused solely on hospital admissions, which may have led to a dataset with similar feature distributions. Nayak et al. conducted a study using the Hungarian, Cleveland, and Switzerland datasets, applying an ANN model with an accuracy of 89.75% [8]. The study highlighted the lack of integration with other machine learning models to form a hybrid predictive framework. Modak et al. applied Infinite Feature Selection and Deep Neural Networks (DNN) to the Cleveland, Hungarian, Switzerland, and Statlog datasets, achieving an accuracy of 87.70% [9]. The study recommended further exploration of frameworks for large-scale datasets. Yilmaz et al. utilized the Data Port dataset, applying LR, RF, and SVM, achieving 86%, 92%, and 89% accuracy, respectively [10]. The study was limited by its reliance on a single small dataset and lack of feature selection specifications. García-Ordás et al. used neural networks on a dataset with 918 cases, achieving 90.9% accuracy [11]. The study noted the use of a single small dataset and the absence of time duration specifications for prediction. Lakshmi et al. applied RF to a dataset containing 700 records and 11 features, achieving 80.4% accuracy [12]. The study recommended incorporating hybrid machine learning models and employing accuracy-enhancing techniques. Sureja et al. tested SVM on two datasets, one containing 303 records and another with 299 records, achieving 98% accuracy [13]. The study recommended further investigation into handling large datasets.

2.2 Ensemble Learning Models

Ensemble learning has become an essential strategy in modern machine learning, particularly for tasks requiring high prediction accuracy and generalization. Rather than relying on a single model, ensemble methods aggregate the predictions from multiple learners, thereby reducing variance, minimizing bias, and improving predictive performance. The most common ensemble techniques include bagging, boosting, stacking, and voting. Each method differs in how it combines base models and how those models are trained. Voting is a widely adopted ensemble strategy, especially in classification problems. It comes in two primary forms: hard voting and soft voting. In hard voting, each classifier in the ensemble casts a vote for a predicted class label, and the majority vote determines the final prediction. This method is straightforward but does not account for the confidence levels of predictions. In contrast, soft voting averages the predicted probabilities from each classifier and selects the class with the highest average probability. This approach often results in better performance, especially when classifiers are well-calibrated. Mohapatra et al. implemented a stacked ensemble learning (EL) model on the Cleveland Heart Disease dataset, incorporating ten distinct classifiers as base learners [14]. Their approach demonstrated superior performance, achieving an accuracy of 92%, highlighting the effectiveness of ensemble learning in improving classification

***Table 1**. Some literatural background*

Authors	Goal of the Research	Contribution of the Paper	Method Used
Hatice and et al. [16]	To improve early skin cancer detection using advanced CNN and attention mechanisms with ensemble learning.	Developed DSCIMABNet model integrating CNN and Multi-Head Attention; proposed a hybrid ensemble model with CLAHE-enhanced data and multiple ML classifiers.	Ensemble Learning with CNN, MHA, and ML models (AdaBoost, DT, SVM, RF, KNN, LR)
Parvin and et al.[17]	To predict network traffic using soft voting across multiple ML models to enhance VANET/V2X communication efficiency.	Demonstrated the effectiveness of soft voting ensemble combining five ML classifiers for traffic prediction.	Soft Voting Ensemble (RF, KNN, NB, SVM, DT)
Rayees and et al.[18]	To improve network anomaly detection by integrating preprocessing, feature engineering, and ensemble learning.	Applied SMOTE, feature selection, and ensemble voting classifier integrating SVM, LR, and DT.	Voting Classifier (SVM, Logistic Regression, Decision Tree), SMOTE for balancing
Elif and et al.[19]	To classify shoulder implant types from X-ray images using ensemble learning.	Combined ViT, DeiT, and Swin transformer outputs via soft and hard voting to improve accuracy.	Soft Voting Ensemble (ViT, DeiT, Swin)
Bhargav Mallampati et al.[20]	To detect brain tumors using segmentation features extracted from MRI and a hybrid ML model.	Proposed a hybrid ensemble model combining KNN and Gradient Boosting using soft voting, with improved results over single models.	Soft Voting (KNN + Gradient Boosting)
Muhammad Usama Tanveer et al.[21]	To detect real-time attacks in IoT using a lightweight and robust ensemble classifier.	Developed Ensemble-Guard IoT using soft voting over GNB, LR, and RF to balance performance and computational cost.	Soft Voting Ensemble (GNB, Logistic Regression, Random Forest)
Annisa and et al.[22]	To assess creditworthiness using LinkedIn data and ensemble soft voting classifiers.	Utilized demographic and behavioral social media data with multiple ML classifiers in a soft voting scheme.	Soft Voting Ensemble (DT, NB, LR, SVM, RF)
Dongqi and et al.[23]	To build an interpretable and high-performing ensemble model for SME credit risk assessment.	Introduced voting optimization, bagging-based oversampling, and feature enhancement for better interpretability and accuracy.	Multi-Stage Ensemble (Soft Voting Optimization, GBDT, RF, AdaBoost, XGBoost, ExtraTree, LightGBM)
Ravi and et al.[24]	To improve chiller fault detection under dynamic and steady-state conditions using ensemble learning.	Developed ELMs using soft voting, showing superior fault detection accuracy and robustness under noise.	Soft Voting Ensemble (Multiple Classifiers)
Harun and et al.[25]	To detect human activities and floor levels in buildings using smartphone sensors and AutoML.	Utilized AutoML to select optimal models and combined them via weighted soft voting.	Weighted Soft Voting, AutoML
Arifur and et al.[24]	To optimize spam detection using hybrid ensembles and Bi-LSTM.	Compared hybrid voting (soft/hard) ensemble and Bi-LSTM, identifying top-performing combinations.	Soft and Hard Voting Ensemble (Top 3 from RF, SVM, CatBoost, etc.)
Ikram and et al.[25]	To predict Remaining Useful Life (RUL) using ACVAE and ensemble classifiers.	Developed ACVAE for feature extraction and used soft voting ensemble for class prediction.	Fusion of Deep Learning (ACVAE) + Soft Voting Ensemble
Divya and et al.[26]	To detect phishing websites using a hybrid ensemble model based on URL features.	Introduced LSD model combining LR, SVM, and DT using soft voting, canopy feature selection, and hyperparameter tuning via grid search.	Soft Voting Ensemble (LR + SVM + DT), Grid Search, Canopy Feature Selection

outcomes. Similarly, Das and Sinha proposed a voting-based ensemble learning model for CVD prediction using the Statlog Heart Disease dataset [15]. Their method achieved an accuracy of 90.74%, outperforming classical classifiers such as K-Nearest Neighbors (K-NN), Support Vector

Machine (SVM), Naive Bayes (NB), Decision Tree (DT), Logistic Regression (LR), and Artificial Neural Networks
(ANN). This study reinforced the advantage of ensemble learning models in enhancing predictive accuracy over traditional machine learning techniques. Ensemble methods have been widely adopted across multiple domains due to their ability to enhance model accuracy, robustness, and generalizability. In the healthcare sector, ensemble techniques have played a vital role in improving disease prediction by combining classifiers such as Random Forest, Logistic Regression, Support Vector Machines, and deep learning models. This integration allows for more accurate and reliable diagnostic outcomes. Beyond healthcare, ensemble learning has also shown strong performance in fields like cybersecurity, where it is effectively used to detect phishing attacks, network anomalies, and intrusion attempts by combining diverse classifiers and utilizing advanced feature selection techniques. These cross-domain applications highlight the significance of ensemble learning as a powerful approach for building robust predictive models. Table 1 presents recent studies that have successfully applied ensemble learning methods.
several limitations persist across existing studies. A significant number of works rely on small and homogeneous datasets, which restrict the generalizability and robustness of the models in diverse clinical settings. Additionally, many studies overlook the importance of hyperparameter optimization, a critical step that can substantially enhance model performance. Another recurring issue is the presence of imbalanced datasets, which often leads to biased predictions, particularly for minority classes. These limitations highlight the need for more comprehensive datasets, improved optimization techniques, and robust strategies to handle class imbalance in future research.

3. Methods

3.1 Methodological Framework

The methodological framework was adopted to develop a robust predictive model for cardiovascular disease (CVD) leveraging machine learning techniques. The study's primary objective is to utilize a combination of clinical and behavioral data to construct a model capable of accurately predicting CVD risk. The methodology involves several crucial steps, including data collection, preprocessing, feature selection, model training, and evaluation. Given the complexities of healthcare data, particular emphasis is placed on addressing key challenges such as data imbalance, ensuring that underrepresented cases do not negatively impact model performance, and model interpretability, allowing healthcare providers to make informed clinical decisions based on the model's predictions.
The predictive model is designed to balance accuracy and explainability, ensuring it is not only statistically robust but also interpretable for practical application in clinical settings. To achieve this, the study utilizes multiple datasets. Machine learning algorithms such as Random Forest (RF), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and ensemble learning models are evaluated to determine their effectiveness in predicting CVD risk. The feature selection process is guided by both statistical methods and domain knowledge from medical research, ensuring that the most relevant risk factors contribute to model predictions. The training and validation of the model are conducted using cross-validation techniques, ensuring robustness and generalizability. Various performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC are employed to comprehensively assess model effectiveness. the study aims to contribute to the advancement of AI-driven CVD prediction models, providing healthcare professionals with a data-driven decision-support tool that enhances early detection and preventive care strategies.

3.2 Data source

Used two datasets

- Framingham Heart datasets. This dataset comprises 4,240 records with 16 features, encompassing clinical and lifestyle variables such as BMI, cholesterol levels, glucose levels, and smoking habits. Its comprehensive nature enables a deeper analysis of long-term cardiovascular risk.
- Cardiovascular Disease Dataset. This dataset comprises around 70,000 patient records related to cardiovascular disease, incorporating demographic details, clinical measurements, and behavioral factors such as smoking, alcohol consumption, and physical activity. Its extensive sample size makes it well-suited for training machine learning models.

3.3 Model development

By combining the predictions of multiple classifiers, ensemble learning techniques aim to improve the accuracy, robustness, and generalizability of predictive models. Unlike traditional approaches that rely on a single model,

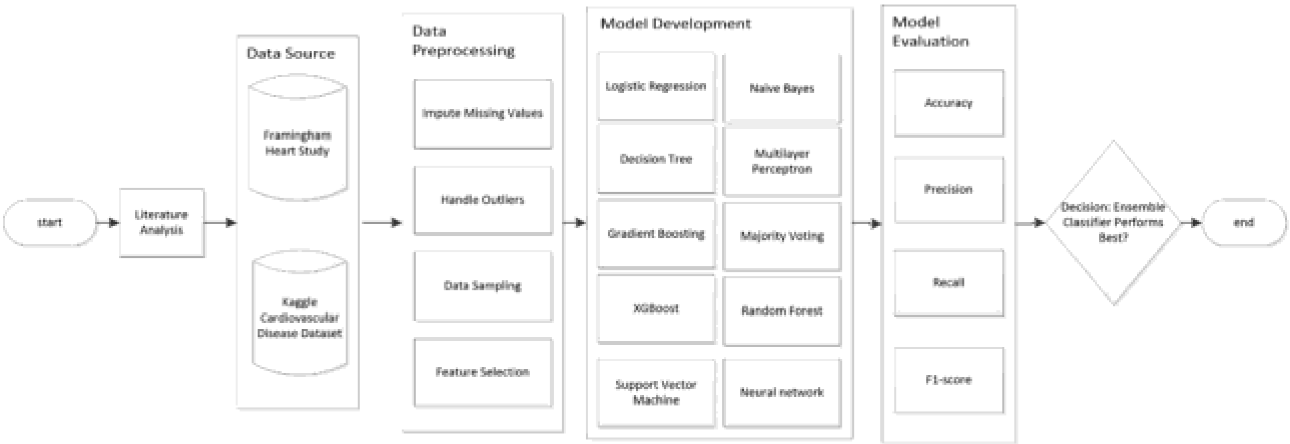

***Figure 1**. The research methodology for this study*

ensemble methods aggregate the outputs of several models to reduce bias, minimize variance, and mitigate the risk of overfitting. In this study, a hybrid ensemble framework was developed using two distinct datasets: the Kaggle Cardiovascular Disease Dataset and the Framingham Heart Study Dataset. Separate models were trained on each dataset, referred to as the Kaggle Model and the Framingham Model, each producing independent probability scores for CVD prediction based on their respective training data. These scores were then integrated through a score-specific weighted soft voting mechanism, allowing for a more nuanced combination of predictions tailored to distinct cardiovascular risk levels. The weighted voting mechanism did not use a fixed weight across all risk categories. Instead, weights were dynamically optimized for each risk score category based on empirical validation:

- Score 1 (low risk): Kaggle (70%), Framingham (30%)
- Score 2 (moderate risk): Kaggle (90%), Framingham (10%)
- Score 3 (high risk): Kaggle (60%), Framingham (40%)

As illustrated in Figure 2, the ensemble architecture begins by processing input features separately through the Kaggle and Framingham pipelines. The resulting probability scores are then passed to the weighted voting module, which computes the final risk prediction. This adaptive mechanism allowed the model to capitalize on the broader statistical patterns from the Kaggle dataset and the clinical depth of the Framingham dataset, leading to substantial performance gains across all risk levels.

4. Results and Discussions

4.1 Key Feature Selection and Analysis Findings

Feature selection plays a pivotal role in constructing interpretable and accurate machine learning models for cardiovascular disease (CVD) prediction. In this study, a medically grounded feature analysis was conducted across the Kaggle and Framingham datasets to identify the most impactful clinical and behavioral predictors. Consistently, features such as age, BMI, systolic and diastolic blood pressure, cholesterol, and glucose emerged as the strongest predictors of CVD, aligning with well-established cardiovascular risk factors. To strengthen the validity and effectiveness of the selected features, two complementary analyses were performed: correlation analysis and feature interaction analysis. Beyond simple pairwise correlations, feature interaction analysis was applied to understand how combinations of features jointly influence CVD risk, particularly in relation to the Score Category framework. The analysis revealed that:

- In Score Category 1 (low risk), interactions among features had minimal impact, as individual indicators remained within normal ranges.
- In Score Category 2 (moderate risk), combinations such as elevated BMI and marginally high cholesterol began to show a compounding effect on risk levels, indicating early-stage risk progression.
- In Score Category 3 (high risk), strong feature interactions especially between high systolic blood pressure and high cholesterol, or glucose and BMI were predominant. These synergistic relationships significantly increased CVD risk and were critical in driving accurate classification in this group.

These results emphasize that not only individual features but also their interactions are vital for robust CVD risk stratification. Recognizing these interactions allowed the model to capture complex, real-world risk profiles, particularly in higher-risk patients where multiple factors often co-exist and interact in harmful ways. In summary, the integration of correlation and interaction analysis with score-based stratification has reinforced the clinical relevance of the selected features while enabling a more nuanced and effective predictive model. This analytical strategy ensures that the model reflects both medical knowledge and data-driven insights, leading to better identification of at-risk individuals across all levels of cardiovascular risk.

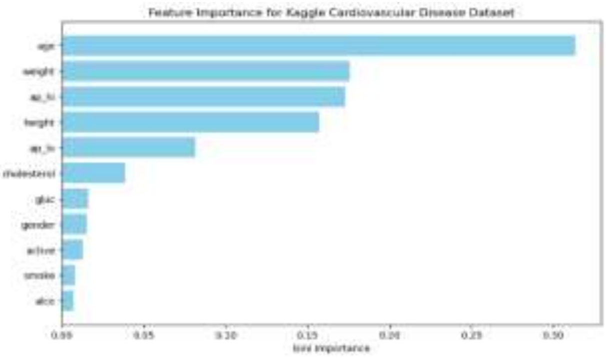

Figure 2. *Feature importance for kaggle cardiovascular dataset*

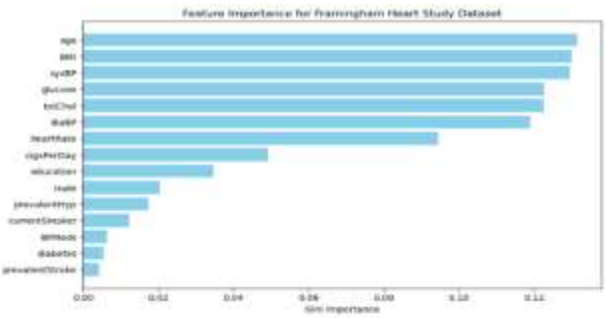

Figure 3. *Feature importance for Framingham heart study dataset*

4.2 Model Performance

The performance of the proposed hierarchical ensemble model demonstrates its ability to predict cardiovascular disease (CVD) risk with high accuracy across multiple risk categories. By leveraging a score-specific weighted voting mechanism, the model integrates the predictive strengths of two complementary datasets Kaggle and Framingham to optimize performance across low-, moderate-, and high-risk groups.

Instead of applying a fixed contribution from each dataset, dynamic weight allocation was implemented per score category, based on empirical results from validation experiments. This approach allowed the model to assign more weight to the dataset that demonstrated superior predictive power for each specific category. The Kaggle dataset provided a broader statistical representation due to its size, while the Framingham dataset added clinical depth and precision. The following table summarizes the final performance metrics across each score category:

These results confirm the effectiveness of the score-adaptive ensemble framework, which delivers high precision and recall across all CVD risk levels.

Table 2. *Obtained results for study*

Score Category	Optimized Weights	Accuracy	AUC	F1 Score
Score 1 (Low Risk)	(0.7, 0.3)	0.9745	0.99	0.97
Score 2 (Moderate Risk)	(0.9, 0.1)	0.83	0.9071	0.83
Score 3 (High Risk)	(0.6, 0.4)	0.93	0.97	0.93

The integration of multi-source data through intelligent voting not only improves overall accuracy but also ensures the clinical relevance and interpretability of the model. This makes it a reliable decision-support tool for early detection and personalized cardiovascular risk assessment in real-world healthcare environments.

4.3 Clinical Relevance and Practical Implications

The findings of this study underscore the clinical utility and practical significance of the proposed hierarchical ensemble model for cardiovascular disease (CVD) prediction. By achieving high and balanced accuracy across multiple risk categories 97.45% for low risk, 83.65% for moderate risk, and 93.24% for high risk the model demonstrates its capacity to support early detection, accurate risk stratification, and effective preventive intervention planning. The model’s architecture, which integrates medical knowledge, robust feature selection, and score-specific weighted voting, reflects a deep alignment with real-world clinical workflows. This adaptive framework not only ensures high sensitivity in identifying high-risk individuals but also maintains precision in classifying low-risk patients, minimizing false positives and unnecessary interventions. From a clinical standpoint, such performance translates into greater diagnostic confidence, enabling healthcare professionals to take proactive measures tailored to each patient’s risk level. The use of clinically validated features (e.g., age, blood pressure, cholesterol, glucose, BMI) and behavioral indicators ensures that predictions are both medically interpretable and actionable.

Moreover, the framework’s ability to balance statistical generalizability (via the Kaggle dataset) with clinical depth (via the Framingham dataset) enhances its applicability across diverse patient populations and healthcare environments. Its flexibility, interpretability, and high performance make it a promising tool for deployment in clinical decision support systems, community health screenings, and personalized care planning. In summary, the model not only delivers technical excellence but also meets the practical requirements for real-world implementation, thereby contributing meaningfully to the advancement of AI-assisted healthcare in cardiovascular disease management. The results highlight the clinical utility of the hierarchical prediction model. Its near-perfect accuracy, coupled with high interpretability and sensitivity, makes it a robust tool for real-world CVD risk prediction. The methodology demonstrates how combining medical knowledge, intelligent data preprocessing, and ensemble learning can significantly improve prediction outcomes in healthcare. This approach supports early detection, personalized risk assessment, and the design of preventive strategies, making it highly applicable for clinical and public health use.

5. Conclusions

This research introduces a comprehensive, clinically informed framework for the prediction of cardiovascular disease (CVD) using advanced machine learning and ensemble learning techniques. By systematically integrating clinical expertise, behavioral risk factors, and robust data-driven methodologies, the study addresses several persistent challenges in CVD prediction namely, data imbalance, and inadequate feature selection. A core contribution of this work is the identification and validation of medically significant features such as age, BMI, blood pressure, cholesterol, and glucose across two well-established datasets: the Kaggle Cardiovascular Disease Dataset and the Framingham Heart Study Dataset. These features, widely recognized in medical literature, were further analyzed through correlation and interaction analysis to ensure statistical soundness, minimize redundancy, and capture complex relationships that impact cardiovascular risk. To enhance performance across varying patient profiles, a Risk Score Category framework was developed, supported by SMOTE and Tomek Links to address class imbalance within each risk group. This strategy enabled the model to improve both sensitivity and generalizability, particularly in underrepresented high-risk categories. Building upon these insights, a hybrid ensemble model using a score-specific weighted soft voting mechanism was implemented. This allowed for dynamic integration of predictive outputs from both datasets assigning optimized weights based on risk category. The final model achieved high accuracy across all categories, with 97.45% accuracy in low-risk (Score 1), 83.65% in moderate-risk (Score 2), and 93.24% in high-risk (Score 3) groups. These results were supported by strong AUC and F1 scores, validating the model’s precision, recall, and clinical reliability. Overall, the proposed framework demonstrates that ensemble learning, when combined with domain-informed feature selection and intelligent data engineering, can yield highly accurate, interpretable, and clinically actionable models. The approach supports early detection, targeted risk stratification, and preventative intervention planning, making it well-suited for integration into real-world clinical decision-support systems and public health applications.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] World Health Organization. *Cardiovascular diseases*. https://www.who.int/health-topics/cardiovascular-diseases/#tab=tab_1

[2] Patidar, S., Kumar, D., & Rukwal, D. (2022). Comparative Analysis of Machine Learning Algorithms for Heart Disease Prediction. *Advances in Transdisciplinary Engineering*. 64-69. https://doi.org/10.3233/ATDE220723

[3] Mansoor, C., Chettri, S. K., & Naleer, H. (2023). Efficient Prediction Model for Cardiovascular Disease Using Deep Learning Techniques. *Migration Letters*. (S13);449-459. https://doi.org/10.59670/ml.v20iS13.6475

[4] Hammadi, J. F., Latif, A. B. A., & Cob, Z. B. C. (2025). Artificial intelligence approaches for cardiovascular disease prediction: a systematic review. *Indonesian Journal of Electrical Engineering and Computer Science*. 38(2);1208-1218. https://doi.org/10.11591/ijeecs.v38.i2.pp1208-1218

[5] Hasanah, U., Soleh, A. M., & Sadik, K. (2024). Effect of Random Under sampling, Oversampling, and SMOTE on the Performance of Cardiovascular Disease Prediction Models. *Jurnal Matematika, Statistika dan Komputasi*. 21(1);88-102. https://doi.org/10.20956/j.v21i1.35552

[6] Khurana, P., Sharma, S., & Goyal, A. (2021). Heart Disease Diagnosis: Performance Evaluation of Supervised Machine Learning and Feature Selection Techniques. *Proceedings of the 8th International Conference on Signal Processing and Integrated Networks, SPIN 2021*. 510-515. https://doi.org/10.1109/SPIN52536.2021.9565963

[7] Mohammad, M. A., Koul, S., Rylance, R., Fröbert, O., Alfredsson, J., Akhtar, Z., Buchebner, D., Erlinge, D., James, S., Varenhorst, C., Szummer, K., Jernberg, T., & Spaak, J. (2022). Development and validation of an artificial neural network algorithm to predict mortality and admission to hospital for heart failure after myocardial infarction: a nationwide population-based study. *Lancet Digital Health*. 4(1);e37-e45. https://doi.org/10.1016/S2589-7500(21)00228-4

[8] Nayak, D. S. K., et al. (2023). Enhancing Cardiovascular Disease Prediction Based on AI and IoT Concepts. *International Journal on Recent and Innovation Trends in Computing and Communication*. 11(10);218-228. https://doi.org/10.17762/IJRITCC.V11I10.8483

[9] Modak, S., Abdel-Raheem, E., & Rueda, L. (2022). Heart Disease Prediction Using Adaptive Infinite Feature Selection and Deep Neural Networks. *4th International Conference on Artificial Intelligence in Information and Communication, ICAIIC 2022 - Proceedings*. 235-240. https://doi.org/10.1109/ICAIIC54071.2022.9722652

[10] Yilmaz, R., & Yağin, F. H. (2022). Early Detection of Coronary Heart Disease Based on Machine Learning Methods. *Medical Records*. 4(1);1-6. https://doi.org/10.37990/medr.1011924

[11] García-Ordás, M. T., Bayón-Gutiérrez, M., Benavides, C., Aveleira-Mata, J., & Benítez-Andrades, J. A. (2023). Heart disease risk prediction using deep learning techniques with feature augmentation. *Multimedia Tools and Applications*. 82(20);31759-31773. https://doi.org/10.1007/s11042-023-14817-z

[12] K. C, L., & C, A. B. (2023). Performance Analysis by Using the Knime Analytical Platform to Forecast Heart Failure Using Several Machine Learning Methods. *International Journal of Research in Applied Science and Engineering Technology*. 11(3);205-211. https://doi.org/10.22214/ijraset.2023.49376

[13] Sureja, N., Chawda, B., & Vasant, A. (2022). A novel salp swarm clustering algorithm for prediction of the heart diseases. *Indonesian Journal of Electrical Engineering and Computer Science*. 25(1);265-272. https://doi.org/10.11591/ijeecs.v25.i1.pp265-272

[14] Reis, H. C., & Turk, V. (2025). DSCIMABNet: A novel multi-head attention depthwise separable CNN model for skin cancer detection. *Pattern Recognition*. 159. https://doi.org/10.1016/j.patcog.2024.111182

[15] Doval Amiri, P. A., & Pierre, S. (2023). A Soft Voting Classification Model for Network Traffic Prediction in VANET/V2X. *International Conference on Wireless and Mobile Computing, Networking and Communications*. 231-236. https://doi.org/10.1109/WiMob58348.2023.10187731

[16] Rafi, R., & Anusha Bamini, A. M. (2024). An Enhanced Ensemble-based Approach for Network Anomaly Detection using Voting Classifier. *8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud), I-SMAC 2024 - Proceedings*. 905-910. https://doi.org/10.1109/I-SMAC61858.2024.10714902

[17] Kablan, E. B. (2024). An Ensemble Voting Approach for Shoulder Implant Classification from X-Ray Images. *2024 47th International Conference on Telecommunications and Signal Processing, TSP 2024*. 92-95. https://doi.org/10.1109/TSP63128.2024.10605940

[18] Mallampati, B., Ishaq, A., Rustam, F., Kuthala, V., Alfarhood, S., & Ashraf, I. (2023). Brain Tumor Detection Using 3D-UNet Segmentation Features and Hybrid Machine Learning Model. *IEEE Access*. 11;135020-135034. https://doi.org/10.1109/ACCESS.2023.3337363

[19] Tanveer, M. U., Munir, K., Amjad, M., Jafar Zaidi, S. A., Bermak, A., & Rehman, A. U. (2024). Ensemble-Guard IoT: A Lightweight Ensemble Model for Real-Time Attack Detection on Imbalanced Dataset. *IEEE Access*. 12;168938-168952. https://doi.org/10.1109/ACCESS.2024.3495708

[20] Mulya, A. D., & Alamsyah, A. (2024). Exploring Creditworthiness Using Social Media Data and Ensemble Soft Voting. *2024 12th International Conference on Information and Communication Technology (ICoICT)*. 29-35. https://doi.org/10.1109/ICoICT61617.2024.10698312

[21] Yang, D., & Xiao, B. (2024). Feature Enhanced Ensemble Modeling With Voting Optimization for Credit Risk Assessment. *IEEE Access*. 12;115124-115136. https://doi.org/10.1109/ACCESS.2024.3445499

[22] Badathala, R. K., Vajapeyayajula, V. R., & Junnuri, R. K. (2024). Hybrid-Ensemble Learning Based Fault Detection and Diagnosis of Chillers. *10th 2024 International Conference on Control, Decision and Information Technologies, CoDIT 2024*. 1613-1618. https://doi.org/10.1109/CoDIT62066.2024.10708526

[23] Jamil, H., Qayyum, F., Iqbal, N., Jamil, F., & Kim, D. H. (2023). Optimal Ensemble Scheme for Human Activity Recognition and Floor Detection Based on AutoML and Weighted Soft Voting Using Smartphone Sensors. *IEEE Sensors Journal*. 23(3);2878-2890. https://doi.org/10.1109/JSEN.2022.3228120

[24] Rahman, A., Parvej, S., Alam, K. S., & Fattah, H. M. A. (2024). Optimizing SMS Spam Detection: Comparative Analysis of Hybrid Voting Ensembles and Bi-LSTM Networks with Stratified Cross-Validation. *Proceedings of the 5th International Conference on Data Intelligence and Cognitive Informatics, ICDICI 2024*. 1030-1035. https://doi.org/10.1109/ICDICI62993.2024.10810777

[25] Remadna, I., Terrissa, L. S., Al Masry, Z., & Zerhouni, N. (2023). RUL Prediction Using a Fusion of Attention-Based Convolutional Variational AutoEncoder and Ensemble Learning Classifier. *IEEE Transactions on Reliability*. 72(1);106-124. https://doi.org/10.1109/TR.2022.3190639

[26] Mohan, D., Amritha, R., & Raj, C. C. (2024). URL based Phishing Detection System using Ensemble of LSD Model. *Proceedings of the 5th International Conference on Data Intelligence and Cognitive Informatics, ICDICI 2024*. 68-73. https://doi.org/10.1109/ICDICI62993.2024.10810953

[27] Mohapatra, S., et al. (2023). A stacking classifiers model for detecting heart irregularities and predicting Cardiovascular Disease. *Healthcare Analytics*. 3;100133. https://doi.org/10.1016/J.HEALTH.2022.100133

[28] Das, T., & Sinha, B. B. (2023). A Comprehensive Study on Machine Learning Methods for Predicting Heart Disease: A Comparative Analysis. *IET Conference Proceedings*. 2023(5);205-210. https://doi.org/10.1049/ICP.2023.1491