CardioLogicX: An Explainable High-Performance Model for Heart Failure Prediction

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***Abstract*—Heart failure is still a significant global health issue, and the key to reducing mortality rates lies in early detection and prompt intervention. This study introduces CardioLogicX, a clinically interpretable ensemble learning framework designed for the binary classification of heart failure, utilizing structured clinical data. The proposed pipeline employs Z-score normalization to standardize feature distributions and Edited Nearest Neighbours (ENN) for balancing classes and minimizing noise. It combines predictions from a diverse stacking ensemble that includes CatBoost, XGBoost, AdaBoost, Extra Trees, and a Multi-Layer Perceptron (MLP) through a Random Forest meta- classifier. The model demonstrates exceptional predictive performance, achieving an accuracy rate of 97.37%, an F1-score of 97%, and an AUC of 0.9896. To enhance interpretability and support clinical judgment, Shapley Additive Explanations (SHAP), offering personalized insights into model decisions, are used to improve interpretability and enhance clinical judgment. Furthermore, comparisons with the leading contemporary methods underscore the model's robustness, diagnostic accuracy, and its potential for real-world medical application.**

Keywords— Heart failure, Ensemble learning, Interpretable AI, SHAP, CDSS

I. INTRODUCTION

Heart failure (HF) describes a decline in the heart's impaired capacity to deliver sufficient blood to meet the body's need. Shortness of breath and edema are some of its symptoms, which are frequently brought on by underlying heart conditions such cardiomyopathy or ischemic illness [1]. According to recent estimates, there will be more than 60 million people worldwide who will have heart failure by 2024. As a result of aging populations and rising cardiovascular risk factors, the burden of heart failure is expected to increase quickly in low- and middle-income nations [2]. Furthermore, a notable regional shift in disease burden is evident in the fact that more than one-third of the world's HF-related years lived with disability (YLDs) currently occur in South and East Asia [3]. The total prevalence of heart failure was 3.6% in population-based research of Icelandic adults aged 66 and over; the prevalence increased with age, with males having much higher rates (5.1%) than women (2.7%). According to forecasts based on demographic trends, the number of older individuals suffering from heart failure may more than quadruple by 2040 and triple by 2060, underscoring the growing burden of heart failure in aging populations [4]. The situation is equally dire in India. According to data from hospitals and the community, HF affects 8–10 million people, or about 1% of the adult population. The prevalence increases to 5–10% in people over 65 and up to 20% in octogenarians [5]. The National Heart Failure Registry (NHFR), covering over 10,850 patients, reports a 22.1% one-year mortality and 17.2% 90- day readmission rate, with mean age at diagnosis in the late 50s, nearly a decade earlier than in high-income populations [6]. The American College of Cardiology / American Heart Association has classified heart failure (HF) clinically into four progressive stages: people at risk but without structural heart disease are in Stage A; people with asymptomatic structural changes are in Stage B; people with structural changes and past or current symptoms are in Stage C; and people with refractory heart failure who need specialized treatment are in Stage D [7]. Early detection is necessary to slow the progression of heart failure and improve clinical outcomes, but early diagnosis remains challenging due to the complex presentation of heart failure, its wide range of symptoms, and regional variations in diagnostic accessibility, particularly in low- and middle-income countries [8].

Given these challenges, there is increasing interest in integrating digital health platforms and AI-enhanced decision support into HF care. These systems utilize a variety of real-world patient data, including imaging, demographics, lab findings, and clinical records, to enhance clinical screening, monitoring, and risk stratification. Such technologies could fill in current gaps in early diagnosis and treatment [9], [10]. In response to the urgent needs highlighted by the increasing incidence of heart failure disease in India and globally, this study explores database-driven, clinically interpretable frameworks for early- stage identification and risk assessment of heart failure with the aim of helping physicians improve prevention, triage, and treatment. The remainder of this paper is organized as follows. Section II presents the literature survey. Section III describes the dataset in detail. Section IV provides a descriptive analysis of the dataset. Section V outlines the proposed methodology and discusses the experimental results. Finally, Section VI concludes the paper and suggests directions for future research.

II. RELATED WORKS

Wang and Cao used a 918-sample UCI dataset to present a bootstrap sampling and weighted fusion LightGBM model for heart failure prediction. Compared to conventional single classifiers, their ensemble approach reduced overfitting, increased recall (88.8%), and attained an accuracy of 86.6%

[11]. Rguig and Chtouki examined ten machine learning algorithms for the prediction of heart failure utilizing the UCI heart disease dataset. LightGBM emerged as the top-performing model, demonstrating excellent predictive capability with an accuracy of 88%, precision of 88%, recall of 93%, and an F1-score of 90% [12]. Karimireddy et al. developed a variety of Bayesian network models using a Kaggle dataset on heart failure that included 746 samples and 12 attributes. The domain knowledge-based network outperformed naive and hill networks with a ROC AUC of 0.846, providing both clinical interpretability and strong predictive performance [13].

Kaur et al. worked on a Support Vector Machine model to a Kaggle-based heart disease dataset. The proposed SVM model achieved 88% accuracy, with strong performance in recall and precision. Their approach emphasized early risk classification and demonstrated the model's utility for high-dimensional clinical data in real-time prediction and personalized treatment planning [14]. Mamun et al. used the UCI heart failure dataset to train various machine learning models including LightGBM, XGBoost, SVM, Logistic Regression, Decision Tree, and Bagging. The dataset comprises 299 samples and 13 clinical features. Using 10-fold cross-validation and SMOTE to address class imbalance, several models were assessed, with LightGBM attaining the best performance of 85% accuracy and an AUC of 0.93, demonstrating significant promise for predicting survival outcomes in patients with heart failure [15].

Zhang and Zhou developed a heart failure prediction model by optimizing an Extreme Learning Machine (ELM) with a Genetic Algorithm (GA). Six key clinical features from the UCI heart failure dataset were focused more. The optimized GA-ELM model achieved a test accuracy of 83.5%, surpassing traditional approaches such as SVM, Decision Tree, and Random Forest. It maintained a quick and effective training process while providing better generalization, higher recall, and more consistent results when compared to the conventional ELM [16]. Kaushik and Birok developed a model to predict mortality in heart failure patients using the XGBoost algorithm. The method was applied to a UCI dataset

that included 12 clinical variables. After hyperparameter tuning with RandomizedSearchCV and Stratified K-Fold, the model achieved 88% accuracy. Utilizing the top four features such as follow-up time, ejection fraction, serum creatinine, and sex identified via permutation importance, accuracy improved to 90%, with reduced overfitting and computational cost [17]. Pandian et al. developed and deployed a machine learning–based heart failure prediction system using four models: Logistic Regression, Decision Tree, K-Nearest Neighbors, and Random Forest. Trained on the Kaggle heart failure dataset with 13 features, the models were optimized using GridSearchCV. Logistic Regression achieved the best results with 89% precision and 92% F1-score. A user-friendly web application was also implemented for real-time predictions using the trained model [18].

Mehta et al. developed a comparative machine learning framework to predict the fatality of heart failure. Various machine learning models, including SVM, Logistic Regression (LR), AdaBoost, Naive Bayes, XGBoost, ExtraTrees, and a Voting Classifier, have been employed. Before training the model, the data underwent preprocessing steps like feature scaling and classification. Among the models, the SVM and Voting Classifier had the highest accuracy (91.67%), followed by Logistic Regression and Naive Bayes, which came in second and third, respectively, at 90%. These findings show how well SVM predicts how heart failure will develop [19]. Wang et al. introduced a multi-task deep and wide neural network (MT-DWNN), trained using electronic health records from over 35,000 heart failure patients. The model performed well, predicting renal dysfunction with an AUC of 0.9393 significantly outperforming traditional models such as logistic regression and random forest. The results emphasize the model's capacity to enhance clinical risk assessment and support medical decision making [20].

Karaoglu et al. optimized Decision Tree, Logistic Regression, and KNN classifiers on a UCI heart failure dataset using 10-fold cross-validation. The Decision Tree achieved the highest accuracy of 84.48%, outperforming past studies and improving reliability in survival prediction of heart failure patients [21]. Newaz et al. developed a Random Survival Forest model for predicting survival risk. Their model attained a concordance index (C-index) of 0.81, outperforming both the traditional Cox and penalized Cox regression models. The most significant factors contributing to survival prediction were serum creatinine, ejection fraction, and patient age [22]. Mirsafaei and Basiri proposed a rule based algorithm called RACER to predict heart failure mortality. Their model achieved an accuracy of 87%, outperforming traditional classifiers such as Random Forest, Support Vector Machine, and Logistic Regression regarding both precision and interpretability [23]. Zhang et al. utilized a Michigan Medicine EHR dataset comprising 300 heart failure patients to create two interpretable models: Standard and Personalized

Logistic Tensor Regression (LTR). Using lab values and medical codes with temporal encoding, the Standard LTR achieved the best results with 0.903 of AUC and 0.836 of AUPRC [24]. Al Younis et al. used machine learning models to classify heart failure patients into HFpEF, HFmEF, and HFrEF using 24- hour ECG circadian features. Using the data gathered from 229 patients across U.S. and Greek cohorts, the decision tree model achieved the highest classification accuracy of 91.2%, outperforming KNN, SVM, and NN models [25]. Huang et al. utilized the MIMIC-IV ICU dataset, which includes 5,073 acute heart failure patient records, to predict mortality using deep neural networks. Backpropagation Neural Network (BPNN) achieved the best results, attaining 94.9% accuracy, outpacing other machine learning and ensemble methods [26]. Lin et al. developed an XGBoost model to assess heart failure risk in 1,220 patients with acute myocardial infarction, using data from Fujian Medical University Hospital. LASSO regression revealed six important features. for training, yielding an impressive AUC of 0.922 and a precision of 89.6%. The model outperformed Random Forest, SVM, and Logistic Regression counterparts [27].

Despite the abundance of heart failure prediction models using diverse datasets and ML techniques, there is limited integration of noise-handling strategies with advanced ensemble architectures for real-time deployment. Few models offer explainability tailored for clinical interpretability alongside high performance. Additionally, cross-dataset generalizability and validation on multi-center real-world EHR data remain underexplored.

III. SUMMARY OF THE DATASET

This study uses the Heart Failure Prediction dataset by Fedesoriano which is available on Kaggle [28]. It integrates data from six distinct sources, including Cleveland, Hungary, Switzerland, Long Beach, Virginia, and Stalog (Heart), originally sourced from the UCI Machine Learning Repository. The dataset is composed of 12 attributes and 918 patient records after removing duplicates. This dataset is designed for binary classification, where the output variable HeartDisease is marked as 1 if heart disease is present and 0 if it is not. The presence of heart disease is interpreted as indicative of heart failure. The dataset includes a variety of demographic, clinical, and diagnostic variables such as age, sex, chest pain type, resting blood pressure, cholesterol levels, ECG results, and exercise-induced indicators. This mix of categorical and continuous features makes it suitable for developing machine learning models. Table I summarizes the dataset attributes.

TABLE I. DESCRIPTION OF DATASET ATTRIBUTES

Attribute	Description
Age	Age of the patient [years]
Sex	Sex of the patient [M: Male, F: Female]
ChestPainType	Chest pain type [TA: Typical Angina, ATA: Atypical Angina, NAP: Non- Anginal Pain, ASY: Asymptomatic]
RestingBP	Resting blood pressure [mm Hg]
Cholesterol	Serum cholesterol [mg/dL]
FastingBS	Fasting blood sugar [1: if > 120 mg/dL, 0: otherwise]
RestingECG	Resting ECG results [Normal, ST-T abnormality, LVH]
MaxHR	Max heart rate achieved [60–202]
ExerciseAngina	Exercise-induced angina [Y: Yes, N:No]
Oldpeak	ST depression induced by exercise
ST Slope	Slope of ST segment [Up, Flat, Down]
HeartDisease	Output class [1: heart disease, 0: Normal]

IV. DESCRIPTIVE METHODOLOGY

Understanding the clinical and demographic distribution of the dataset provides valuable context for heart failure prediction. Fig. 1 presents the distribution of patients by sex and heart failure status. As seen in Fig. 1(a), males constitute 79% of the population, while females represent only 21%. The overall prevalence of heart failure is 55.3%, illustrated in Fig. 1(b). Among the male population, 63.2% were affected Fig. 1(c), compared to only 25.9% among females Fig. 1(d), indicating a notable sex-based disparity.

Fig. 2 shows the prevalence of heart failure across various levels of ST depression induced by exercise (Oldpeak). The highest patient concentration occurs at a value of 0. Most affected individuals fall between 0.1 and 2.0, suggesting that mild to moderate ST depression is more frequently associated with heart failure. A sharp decline in affected cases beyond 3.0 implies that more severe ST depression is less common.

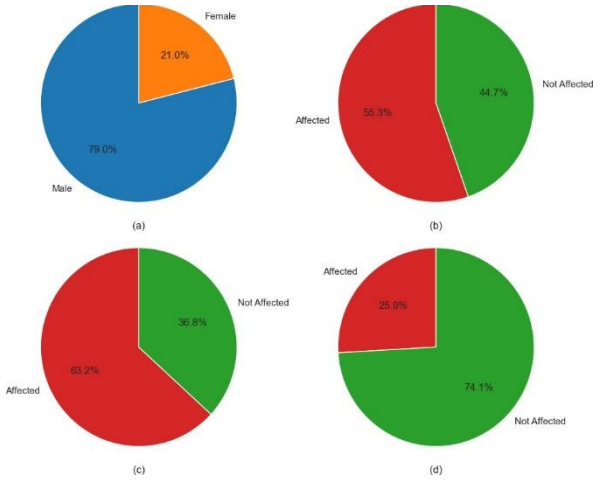

Fig. 1. Demographic breakdown and heart failure prevalence by sex.

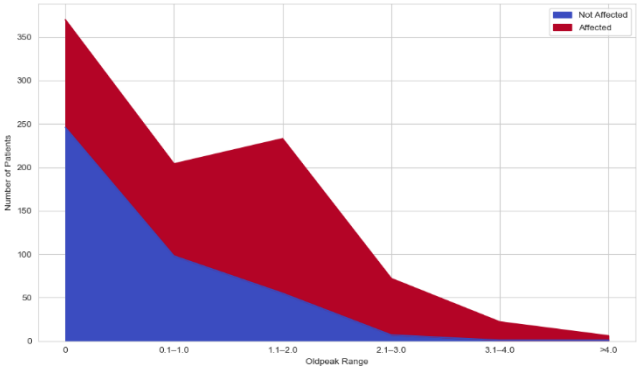

Fig. 2. Distribution of heart failure cases across Oldpeak (exercise-induced ST depression) values.

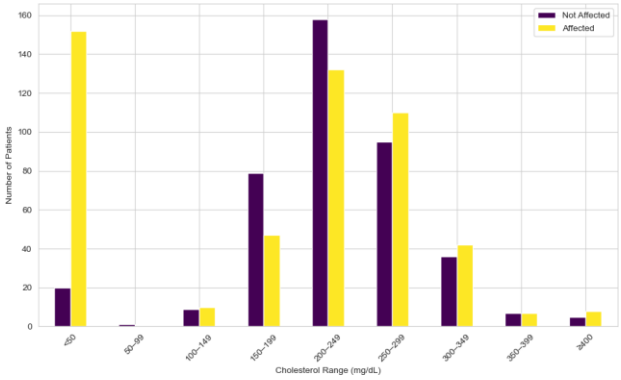

Fig. 3. Heart failure distribution across cholesterol level intervals

Fig. 3 displays cholesterol values grouped into 50 mg/dL intervals. The highest number of heart failure cases (152 patients) occurred in the group with cholesterol levels below 50 mg/dL, followed by 132 cases in the 200–249 mg/dL range and 110 in the 250–299 mg/dL range. This U-shaped trend implies that both extremely low and elevated cholesterol levels may increase susceptibility to heart failure.

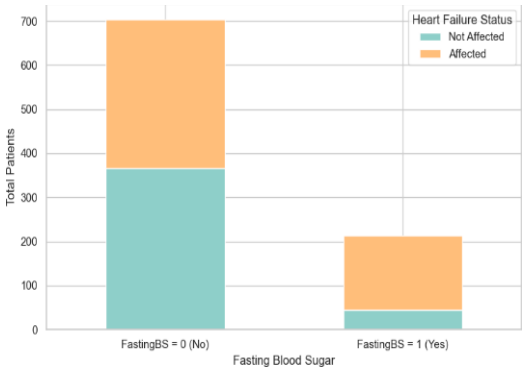

Fig. 4. Heart failure prevalence based on fasting blood sugar levels

The impact of fasting blood sugar on heart failure prevalence is shown in Fig. 4. Among patients with elevated fasting blood sugar, 79.4% experienced heart failure, while only 35.1% of patients with normal glucose levels were affected. This highlights the strong association between impaired glucose regulation and cardiovascular risk.

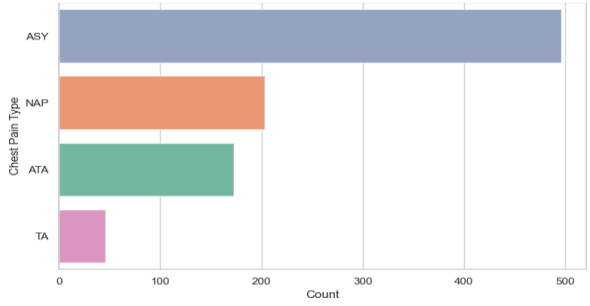

Fig. 5. Heart failure rate across different types of chest pain

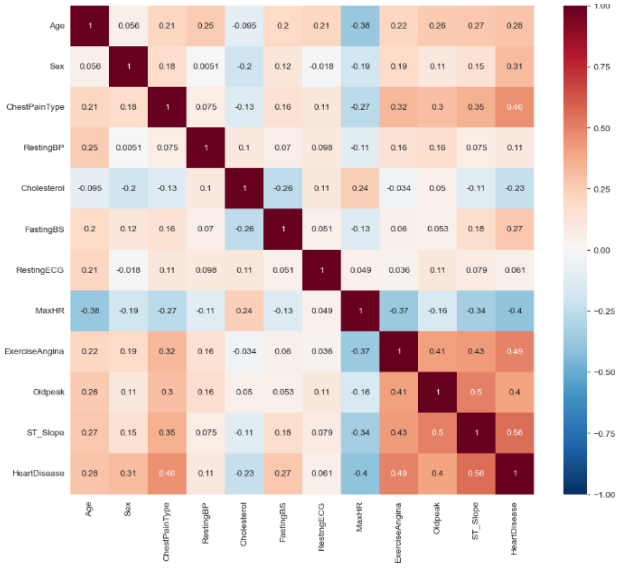

Fig. 6. Correlation heatmap of clinical features with heart failure

Chest pain type and its relationship to heart failure are examined in Fig. 5. Patients presenting with asymptomatic (ASY) chest pain exhibited the highest rate of heart failure (79%), followed by typical angina (TA) at 43.5%, non-anginal pain (NAP) at 35.5%, and atypical angina (ATA) at 13.9%. These patterns suggest that even the absence of classic chest pain can indicate a higher underlying risk. Finally, Fig. 6 shows a correlation heatmap of key clinical variables. Darker red shades reflect strong positive associations with heart disease for features like ST Slope, ChestPainType, ExerciseAngina, and Oldpeak, while blue tones highlight negative correlations for variables such as MaxHR and Cholesterol. These insights support the clinical relevance of these features in prediction of heart failure.

V. Proposed Methodology

The proposed framework, CardioLogicX, is a machine learning pipeline developed for prediction the heart failure. It adopts a stacking ensemble architecture where multiple base learners are trained independently, and their outputs are fused through a Random Forest meta-classifier. It enables the model to capture diverse patterns while improving predictive robustness. The overall workflow includes data preprocessing, noise reduction and class balancing, ensemble training, and post-hoc interpretability, as depicted in Fig. 7.

During preprocessing, categorical features such as sex and chest pain type were numerically encoded using fixed mappings aligned with clinical semantics (e.g., sex: male as 1, female as 0), while continuous variables were standardized using Z-score normalization to ensure zero mean and unit variance. This normalization enhances training stability and improves convergence during model optimization.

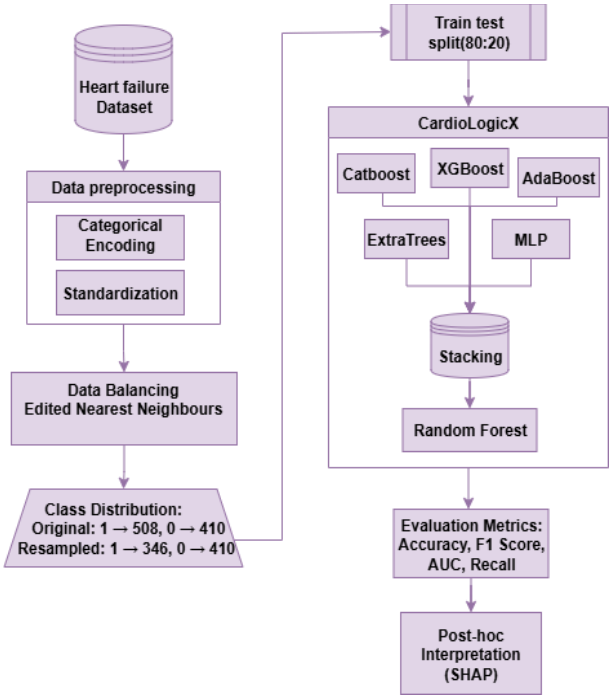

Fig. 7. CardioLogicX pipeline for heart failure prediction

To address class imbalance and reduce noise, the Edited Nearest Neighbours (ENN) algorithm was employed. ENN removes samples from the majority class whose labels differ from those of their nearest neighbors, thereby enhancing class separability. Initially, the dataset contained 508 instances from the affected class and 410 from the not affected class. After ENN-based undersampling, the affected class was reduced to 346 samples, while the not affected class remained unchanged. The complete process is formalized in Algorithm 1, which outlines each stage from preprocessing and ENN-based noise reduction to base learner training and final meta-classification.

A. Algorithm 1: CardioLogicX

Input: Raw dataset D with features x , mean μ, standard deviation σ, train-test split ratio

Output: Predicted labels $\hat{y}$, evaluation metrics

1. $Encode\ categorical\ features\ using\ domain-informed\ mapping$
2. $Standardize\ continuous\ features\ using\ Z-score\ normalization$

$$Z = \frac{x - \mu}{\sigma}$$

3. $Apply\ Edited\ Nearest\ Neighbours\ (ENN)$:
   3.1 $for\ each\ instance\ x_i \in D$:
      3.1.1 $Identify\ k-nearest\ neighbors\ of\ x_i$
      3.1.2 If majority label $\neq$ label of x_i, remove x_i
      3.1.3 $End\ loop$
      3.1.4 $Let\ D_{bal}\ be\ the\ resulting\ balanced\ dataset$
4. $Split\ D_{bal}\ into\ training\ and\ testing$
5. $For\ each\ base\ model\ M_i \in \{CatBoost, XGBoost, AdaBoost, Extra\ Trees, MLP\}$:
   5.1 $Train\ M_i\ on\ D_{train}$
   5.2 $Predict\ class\ probabilities\ p_i(x) on\ D_{test}$
6. $Construct\ Meta-Feature\ Matrix$
      6.1 $Combine\ output\ probabilities$:
      6.2 $Meta-feature\ matrix = \{p_1(x), p_2(x), \dots, p_n(x)\}$
7. $Train\ metaclassifier\ M_{meta}(Random\ Forest)\ on\ meta-feature\ matrix$
8. $For\ each\ test\ instance\ x$:
   8.1 $Predict\ the\ final\ class\ label\ using\ the\ meta-classifier$: $M_{meta}\{\{p_i(x)\}\}$
9. $Evaluate\ \hat{y}$

End Algorithm

After resampling, the dataset is split into training and testing sets using an 80:20 ratio. A diverse ensemble of base classifiers such as CatBoost, XGBoost, AdaBoost, Extra Trees, and Multi-Layer Perceptron (MLP) are independently trained on the training data. Each base learner generates class probabilities, which are then concatenated to form a meta-feature space. A Random Forest model is trained on this meta-level representation to generate the final prediction. The stacked approach enables the framework to leverage complementary strengths of heterogeneous learners for improved generalization in heart failure prediction.

To ensure clinical trust and interpretability, SHAP (SHapley Additive exPlanations) is incorporated for post-hoc model explanation. SHAP assigns attribute values to each feature based on its contribution to an individual prediction. These values are visualized using waterfall plots, which show how specific features influence the decision toward predicting heart disease or heart failure. Such interpretability is crucial in a clinical context, helping practitioners understand the rationale behind model decisions and validating their alignment with established medical knowledge. Through SHAP, CardioLogicX provides both predictive accuracy and transparent decision making, positioning it as a reliable tool for cardiovascular risk assessment.

VI. Results and Discussion

The CardioLogicX model integrates a diverse set of base classifiers such as CatBoost, XGBoost, AdaBoost, Extra Trees and a Multi-Layer Perceptron that are trained independently to capture various aspects of the data distribution. Each model generates probability outputs for classification, which are then aggregated into a meta-feature space. A Random Forest metaclassifier is subsequently trained in this meta-space predictions, correct individual model errors, and produce the final output. The stacked ensemble structure improves both generalizability and predictive performance in diagnosing heart disease and heart failure from clinical data.

TABLE II. Classification Report of CardioLogicX

Class	Precision	Recall	F1-Score	Support
Not Affected	1.00	0.94	0.97	68
Affected	0.95	1.00	0.98	84
Accuracy	–	–	0.9737	152
Macro Avg	0.98	0.97	0.97	152
Weighted Avg	0.97	0.97	0.97	152

As shown in Table II, the model achieves an overall accuracy of 97.37%, with an F1-score of 98% for the affected class and 97% for the not affected class. The macro-averaged precision and recall are 98% and 97% respectively, indicating strong and balanced performance across both classes.

Fig. 8 highlights the low misclassification rate of the CardioLogicX model, with the majority of predictions aligning accurately with true labels. This demonstrates the model's strong capability in correctly distinguishing between affected and not affected cases. The minimal number of false positives and false negatives reflect high classification reliability. Moreover, the ROC curve shown in Fig. 9 confirms the model's excellent discriminatory performance, achieving an area under the curve (AUC) of 0.9896. Such a high AUC value indicates that the model maintains both high sensitivity and specificity across various classification thresholds. Together, these results affirm the robustness and clinical potential of CardioLogicX in heart failure prediction tasks.

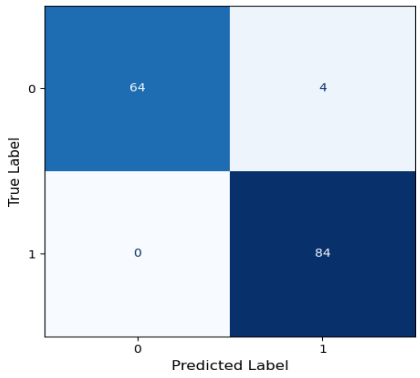

Fig. 8. Confusion Matrix – CardioLogicX Model

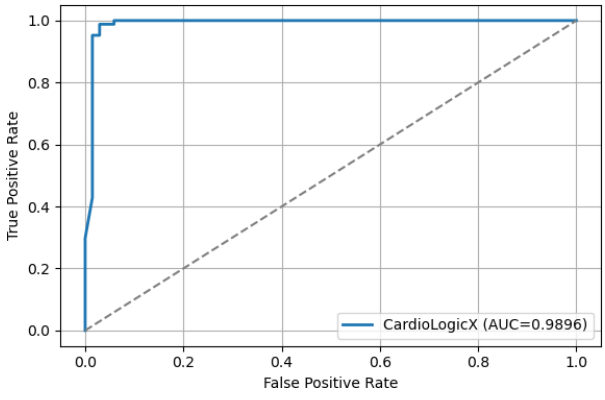

Fig. 9. ROC curve – CardioLogicX Model

As detailed in Table III, the proposed model outperforms several recent approaches that utilize deep learning, traditional machine learning, or hybrid strategies for heart failure prediction. While previous methods achieved respectable performance through feature selection, data augmentation, or noise filtering, none matched the accuracy and robustness of CardioLogicX. These findings reinforce the value of integrating Edited Nearest Neighbours for noise reduction with a strategically designed ensemble learning pipeline.

TABLE III. COMPARISON WITH EXISTING APPROACHES

S. No.	Author(s)	Model Description	Result
1	Tamizharasi et al. [29]	SimCLR with GAN-based augmentation	Accuracy: 91.04%, CV: 95.4%
2	Sonam Nagar et al. [30]	Optimized KNN (K=15) with multi-feature selection	Accuracy: 89.49%, ROC-AUC: 0.89
3	Tabassum et al. [31]	XGBoost with Isolation Forest for noise handling	Accuracy: 94.34%, F1-score: 95.19%
4	Vinod Jain [32]	Cross-validated Random Forest on UCI dataset	Accuracy: 92.86%
5	Lutfi and Shidik [33]	KNN with ENN and feature scaling	Accuracy: 92.61%
6	**CardioLogicX – Proposed**	ENN with Stacked Ensemble (Random Forest as meta)	**Accuracy: 97.37%, AUC: 0.9896, F1-score: 97%**

Although the proposed model performs exceptionally well, inter- pretability is critical for clinical acceptance. In real-world medical contexts, transparency in predictions fosters trust and facilitates collaboration between clinicians and machine learning systems. To enhance interpretability, SHAP (SHapley Additive exPlanations) was employed to provide feature-level insights into the model's decision process.

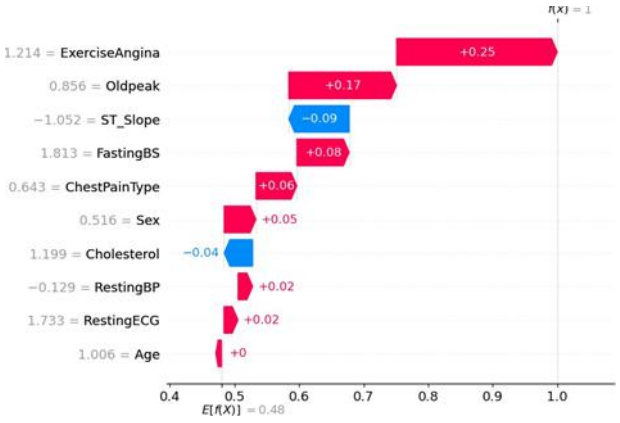

Fig. 10. SHAP waterfall plot for a patient predicted as affected.

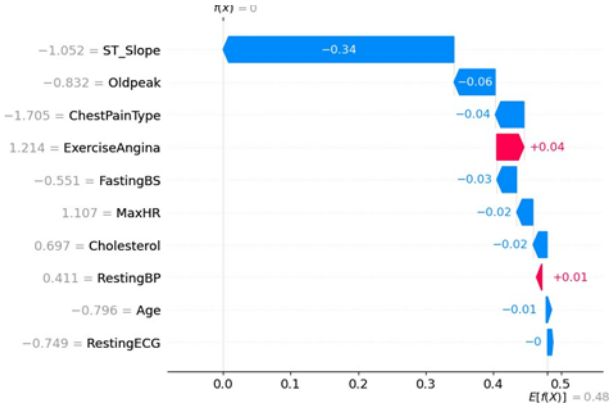

Fig. 11. SHAP waterfall plot for a patient predicted as not affected

Figs. 10 and Fig. 11 illustrate how SHAP values attribute importance to individual features for two example cases. In the affected case, attributes such as ExerciseAngina, Oldpeak, and FastingBS strongly influenced the outcome. Conversely, for the not affected case, ST_Slope, ChestPainType, and Oldpeak were the main factors leading to a negative prediction. These explanations are consistent with established medical understanding and support the reliability of the model in clinical settings.

The effectiveness of the CardioLogicX framework lies in its robust classification capability, balanced handling of class distributions, and reliable generalization across patients with and without heart failure. Its transparent decision making process, supported by SHAP-based explanations, enhances clinical trust and interpretability, positioning it as a high utility model for both heart disease and heart failure prediction.

VII. CONCLUSION

Cardiovascular diseases, including heart failure, pose a continuous global health challenge, requiring precise and comprehensible diagnostic instruments. This study introduced CardioLogicX, a machine learning framework designed to predict heart failure using a stacked ensemble of diverse classifiers. The model employs Edited Nearest Neighbours for noise reduction and addressing class imbalance and integrates predictions from multiple base learners using a Random Forest meta-classifier. It achieved reliable performance across both affected and unaffected cases, with an overall accuracy of 97.37%. Post-hoc interpretability was enabled through SHAP, which provided feature-level insights to help clinicians understand individual predictions and improve trust in the system.

Future enhancements will focus on integrating deep neural network models within the ensemble to capture more complex data patterns and interactions. The incorporation of genetic information is also planned to support personalized cardiovascular risk prediction. Additionally, efforts will be made to ensure real-time clinical deployment and integration into decision support systems. These developments are expected to further strengthen the clinical relevance and predictive accuracy of CardioLogicX for heart failure detection.

REFERENCES

[1] Shams, P., Malik, A., & Chhabra, L. (2025, February 26). *Heart failure (congestive heart failure)*. StatPearls Publishing. https://www.ncbi.nlm.nih.gov/books/NBK430873/

[2] Chen, Q.-F., Liu, F.-F., Li, W., Zhou, Y.-J., & Li, J.-W. (2025). Global burden of heart failure and its underlying causes in 204 countries and territories, 1990–2021. *European Heart Journal – Quality of Care and Clinical Outcomes*.

[3] Ran, J., Li, Y.-C., Liu, Y.-Q., Zhao, Z.-Y., & Chen, H. (2025). Global, regional, and national burden of heart failure and its underlying causes, 1990–2021. *Biomarker Research, 13*(16).

[4] Danielsen, R., Aspelund, T., Eiriksdottir, G., Gudnason, V., & Launer, L. J. (2017). Prevalence of heart failure in the elderly and future projections: The AGES-Reykjavík study. *Scandinavian Cardiovascular Journal, 51*(4), 183–189.

[5] Indian College of Cardiology. (2025). *The current situation*. National Heart Failure Registry, India. https://www.iccnhfr.org/the-current-situation

[6] Harikrishnan, S., Narasimhan, C., Karthikeyan, G., Khanna, S., & Vaithilingam, S. (2025). One-year mortality and re-admission rate by disease etiology in National Heart Failure Registry of India. *Nature Communications, 16*(275).

[7] Health.com Editors. (2024, March 20). *The stages of congestive heart failure*. Health.com. https://www.health.com/congestive-heart-failure-stages-8672968

[8] Savarese, G., & Lund, L. H. (2017). Global public health burden of heart failure. *Cardiac Failure Review, 3*(1), 7–11.

[9] Medhi, D., Pathak, R., Sharma, N., & Sinha, A. (2024). Artificial intelligence and its role in diagnosing heart failure: A narrative review. *Cureus, 16*(5), e59661.

[10] Gala, D., Mehta, P., & Shah, A. (2024). The role of artificial intelligence in improving patient outcomes and future of healthcare delivery in cardiology. *Healthcare (Basel), 12*(4), 481.

[11] Wang, Y., & Cao, H. (2025). Heart failure prediction based on bootstrap sampling and weighted fusion LightGBM model. *Applied Sciences, 15*(8), 4360.

[12] Rguig, A., & Chtouki, D. Y. (2025). Machine learning models in predicting heart failure based on patient data. In *Proceedings of ICoCSETI* (pp. 706–709).

[13] Karimireddy, S. S. R., Vardhan, H., & Shukla, A. P. (2025). Heart disease risk assessment using Bayesian networks. In *Proceedings of AIDE* (pp. 286–290).

[14] Kaur, A., Kaur, S., & Kaur, H. (2024). Safeguarding hearts using SVM for early heart disease prediction. In *Proceedings of ASIANCON* (pp. 1–4).

[15] Mamun, M., Zaman, F., & Sultana, N. (2022). Heart failure survival prediction using machine learning algorithm. In *Proceedings of AIIoT* (pp. 194–200).

[16] Zhang, S., & Zhou, W. (2021). Prediction model of heart failure disease based on GA-ELM. In *Proceedings of CCC* (pp. 7944–7948).

[17] Kaushik, S., & Birok, R. (2021). Heart failure prediction using XGBoost. In *Proceedings of ICECCT* (pp. 1–6).

[18] Pandian, K. A., Rajasekar, D., & Ravi, A. (2021). ML model for automatic heart failure prediction. In *Proceedings of ASIANCON* (pp. 1–6).

[19] Mehta, D., Patel, R., & Shah, H. (2021). Death by heart failure prediction using ML algorithms. In *Proceedings of ICNTE* (pp. 1–5).

[20] Wang, B., Liu, W., Zhang, J., & Chen, X. (2019). A multi-task neural network for renal dysfunction prediction. *IEEE Access, 7*, 178392–178400.

[21] Karaoglu, A. N., Demir, A. E., & Ozkan, H. (2021). Decision tree in predicting heart failure. In *Proceedings of UBMK* (pp. 781–784).

[22] Newaz, A., Alvi, F. S., Alam, S., & Rahman, R. (2021). Risk prediction in heart failure using random survival forest. In *Proceedings of ICEEICT* (pp. 1–6).

[23] Mirsafaei, M., & Basiri, A. (2022). Addressing death from heart failure using RACER algorithm. In *Proceedings of ICEE* (pp. 636–640).

[24] Zhang, Y., Li, Z., Wang, W., & Liu, J. (2024). Interpretable ML models for advanced therapy prediction using EHR data. *BMC Medical Informatics and Decision Making, 24*(1), 53.

[25] Al Younis, S. M., Ahmed, L., & AlGhamdi, F. (2024). Prediction of heart failure with different LVEF using circadian ECG and ML. *PLOS ONE, 19*(5), e0302639.

[26] Huang, J., Zhao, X., Zhang, L., & Yu, P. (2024). Prediction of mortality events of AHF patients in ICU using DNN. *Computer Methods and Programs in Biomedicine, 256*, 108403.

[27] Lin, Q., Wu, J., Zhou, F., & Li, X. (2025). Risk of HF after AMI using interpretable ML model. *Frontiers in Cardiovascular Medicine, 12*, 1444323.

[28] Soriano, F. (2021). *Heart failure prediction [Data set]*. Kaggle. https://www.kaggle.com/datasets/fedesoriano/heart-failure-prediction

[29] Thakur, A. G. S., Patel, V. R., & Shah, D. R. (2024). Prediction of heart failure using enhanced self-supervised learning. In *Proceedings of IIPEM* (pp. 1–6).

[30] Nagar, S., Singh, H., & Kumar, A. (2025). Next-gen cardio care: Hyperdimensional K in KNN prognosis. *Procedia Computer Science, 258*, 4257–4268.

[31] Tabassum, S., Anwar, A., & Rashid, F. (2025). ML-based framework for heart disease diagnosis. *Computer Modeling in Engineering & Sciences, 84*(1), 1253–1278.

[32] Jain, V. (2023). Heart failure prediction using ML algorithms with cross validations. In *Proceedings of ICCPCT* (pp. 1420–1423).

[33] Lutfi, D. K., & Shidik, G. F. (2023). Improvement heart failure prediction using binary preprocessing. In *Proceedings of ICAMIMIA* (pp. 236–241).