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Ensemble Learning based Cardiovascular Disease Prediction Combining with Predictive Analytics & Risk Stratification

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Abstract:

Heart failure continues to be a significant contributor to illness and death on a global scale, highlighting the need for effective strategies in early detection and risk stratification. Therefore, the study presents an efficient approach to heart failure prediction by integrating predictive analytics with advanced risk stratification techniques. This study develops and evaluates a novel ensemble learning-based predictive model that combines machine learning algorithms with clinical and demographic data to enhance early diagnosis and risk assessment. The proposed model leverages multiple data sources, such as electronic health records and patient history, to identify critical predictors and generate actionable insights. This study demonstrates significant improvements in prediction accuracy compared to GBC, RF, LR, DTC, and MLP 4%, 4%, 6%, 5%, and 4%, respectively, with enhanced capability to identify high-risk individuals before the onset of severe symptoms. By integrating these predictive and stratification techniques, the study offers a robust framework for early intervention and personalized treatment, ultimately contributing to better management of heart failure and improved patient outcomes. These findings show the potential of combining advanced analytics with clinical expertise to advance heart failure prediction and management.

Keywords: Cardiovascular Disease, Electronic Health Record(EHR), Ensemble, Heart Failure, Machine Learning, Random Forest.

1. Introduction

Heart failure (HF) is a complex and critical public health issue characterized by the heart's inability to pump blood efficiently, leading to significant morbidity, mortality, and a heavy burden on healthcare systems worldwide [1]. HF affects millions of individuals, and its prevalence continues to rise due to factors such as aging populations, lifestyle changes, and increasing rates of cardiovascular diseases. This growing global health concern underscores the need for innovative approaches to early detection, accurate diagnosis, and effective management of HF. Traditional diagnostic methods, which often identify HF at its later stages when symptoms are more severe, limit the potential for early treatment and intervention, resulting in poorer patient outcomes and higher healthcare costs [2], [3].

Recent advancements in predictive analytics and machine learning present promising opportunities to address these challenges by enhancing the accuracy and timeliness of HF prediction [4], [5]. Predictive models that leverage diverse data sources, including electronic health records (EHRs), patient

demographics, clinical history, and lifestyle data, offer a more comprehensive assessment of a patient's risk profile. These models are capable of identifying patterns, correlations, and risk factors that traditional diagnostic methods may overlook. By employing machine learning algorithms, it becomes possible to predict HF at an earlier stage, thus enabling clinicians to implement preventive measures and more personalized treatment plans. Early detection through predictive analytics can potentially reduce the progression of HF and improve the quality of life for patients.

A key component of effective HF management is risk stratification, which involves categorizing patients based on their likelihood of developing HF or experiencing adverse outcomes. Accurate risk stratification is essential for healthcare providers to prioritize clinical interventions, allocate resources efficiently, and tailor treatment plans to individual patient needs [6]. Current risk stratification techniques often lack the precision required for personalized care and may not fully utilize the vast amount of available healthcare data. As a result, there is a need for more sophisticated models that integrate advanced analytics with robust risk stratification methods.

The objective of this research is to develop and evaluate an integrated approach that combines predictive analytics with ensemble learning techniques to enhance HF prediction and risk stratification. Ensemble learning, which aggregates the predictive capabilities of multiple machine learning models, has been shown to improve accuracy and robustness in various predictive tasks. By leveraging ensemble methods, this study aims to create a predictive model that not only outperforms traditional diagnostic approaches but also delivers more reliable and actionable insights into patient risk. The proposed model will utilize a broad array of clinical and demographic data to build a holistic framework for HF prediction, enabling earlier identification of high-risk individuals and supporting personalized treatment strategies.

This research also seeks to bridge the gap between advancements in machine learning and their practical application in real-world clinical settings. Despite the potential of predictive analytics, its integration into routine clinical practice for HF prediction remains limited. Many predictive models are developed in research settings but are not widely adopted due to challenges related to implementation, validation, and clinician usability. Therefore, this study focuses not only on the development of a predictive model but also on ensuring its practical applicability and scalability in healthcare environments.

By integrating predictive analytics with advanced risk stratification techniques, this study aims to contribute to more effective and personalized HF management. The proposed model will support earlier intervention, allowing healthcare providers to implement preventive measures before the onset of severe symptoms, ultimately improving patient outcomes and optimizing resource allocation within healthcare systems. This research has the potential to significantly advance the field of HF prediction by providing a comprehensive, data-driven framework that enhances predictive accuracy, facilitates early diagnosis, and enables personalized care.

2. Method

Research in HF prediction has evolved significantly, leveraging various methodologies and technologies to enhance early detection and management. This section reviews key studies and methodologies related to predictive analytics and risk stratification in HF.

2.1. Traditional Predictive Models

Early HF prediction methods primarily relied on statistical models and risk scoring systems [7], [8]. Widely used models, such as the Framingham Risk Score [9] and the Chicago Heart Association (CHA) risk score [10], estimate HF likelihood based on traditional risk factors like age, hypertension, and diabetes. However, these models often lack the precision needed for early detection and personalized risk assessment.

2.2. Machine Learning (ML) in HF Prediction

Recent advancements in ML have improved HF prediction accuracy. Various models, such as decision trees (DTs), support vector machines (SVMs), and XGBoost classifiers (XGBC), analyse large datasets to identify complex patterns associated with HF [11], [12]. For example, Ganie et al. [13] showed that ensemble methods and gradient boosting significantly enhance prediction performance over traditional models.

2.3. Deep Learning (DL) in HF Prediction

DL models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have advanced HF prediction further [14], [15], [16]. Guo et al. [17] demonstrated that deep neural networks analysing electronic health records (EHRs) improve HF onset prediction accuracy by capturing complex relationships within extensive datasets.

2.4. Risk Stratification and Personalization

Risk stratification models aim to categorize patients based on their likelihood of risk. These models categorize patients based on HF risk to enable targeted interventions. Sophisticated algorithms, such as clustering and Bayesian networks [18], have refined this process. Strianese et al. [19] showed that integrating clinical data with genetic information enhances risk stratification and personalized treatment.

2.5. Integration of Predictive Analytics and Clinical Practice

Despite advancements, there is a gap in integrating predictive models into clinical Despite advancements, integrating predictive models into clinical practice remains challenging. Azizi et al. [20] noted difficulties in translating predictive analytics into actionable clinical tools, highlighting the need for models that are both accurate and practical for real-world use.

2.6. Comprehensive Approaches and Novel Frameworks

Recent studies advocate for frameworks that combine predictive analytics with risk stratification for comprehensive HF management [21], [22]. Adewole et al. [23] proposed a model that integrates predictive analytics with real-time monitoring to enhance early detection and personalized risk assessment. This research advances these methods by introducing a novel approach that merges advanced machine learning with risk stratification to boost HF prediction accuracy and clinical relevance.

3. Materials and Methods

3.1. Model architecture

The proposed model architecture integrates predictive analytics with risk stratification to enhance HF prediction described in Figure 1.

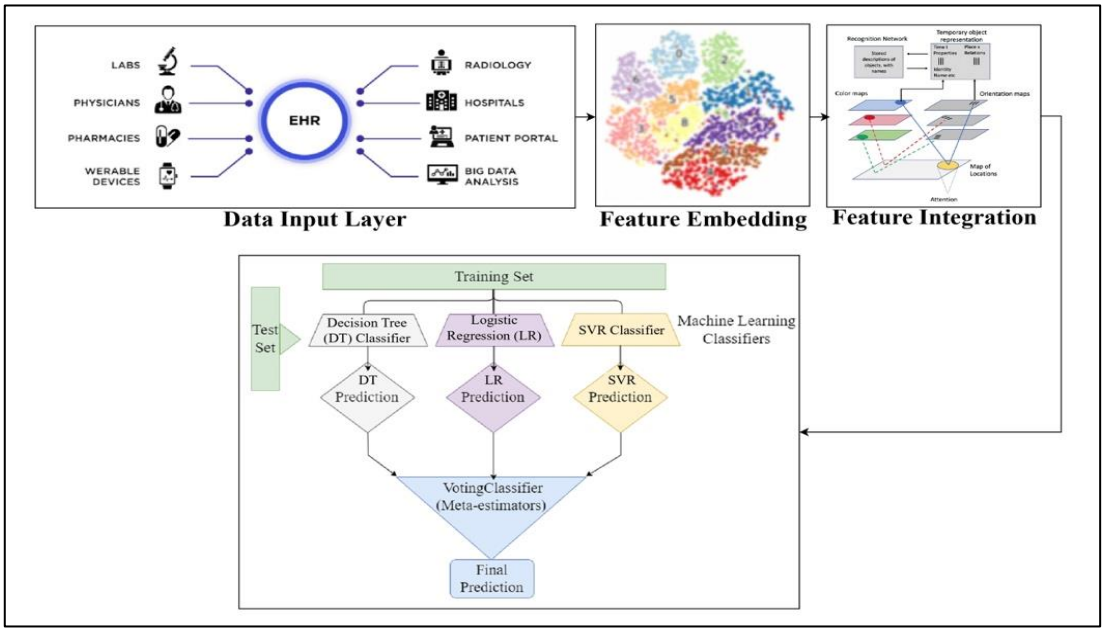
This architecture consists of the following key components:

3.1.1. Data Input Layer

The model begins with an input layer that accepts diverse data sources, including EHRs, clinical metrics, and patient demographics.

Let **X** represent the input feature matrix with n samples, where each sample $\mathbf{x}_i \in R^m$ includes features such as age, blood pressure, and lab results.

Figure 1. Model Architecture of the Proposed Model



3.1.2. Feature Embedding

To handle the heterogeneous nature of the input features, an embedding layer transforms categorical features into continuous vectors. This process captures the underlying relationships and interactions between different features. For a categorical feature x_i^c, the embedding function ϕ maps it to a continuous vector.

$$e_i^c = \phi(x_i^c) \quad (1)$$

where, $e_i^c \in \phi R^d$ is the embedding vector.

3.1.3. Feature Integration

The embedded features are concatenated with continuous features to form a unified feature vector h_i

$$h_i = \text{concat}(x_i^c, x_i^c, e_i^c) \quad (2)$$

3.1.4. Ensemble Network

The integrated feature vector h_i is passed through a series of layers within the ensemble network, enabling the proposed model to learn complex patterns and interactions. The architecture consists of:

$$h_i \rightarrow Layer_1 \rightarrow Layer_2 \rightarrow \ldots \rightarrow Layer_n \quad (3)$$

3.1.5. Output Layer

The final layer is a logistic regression layer that outputs the probability $P(y_i = 1 | \boldsymbol{x}_i)$ of HF for each patient. The output is computed using a sigmoid activation function:

$$\hat{p}_i = \sigma(w_o \boldsymbol{h}_i^{(2)} + b_o) \quad (4)$$

where, σ is the sigmoid function, w_o is the weight matrix, and b_o is the bias term.

3.1.6. Risk Stratification

Based on the predicted probabilities $\hat{p}_i$, patients are classified into different risk categories. The risk stratification is performed using thresholds τ_k defining categories C_k as:

$$C_k = \{\boldsymbol{x}_i \mid \tau_{k-1} < \hat{p}_i \leq \tau_k\} \quad (5)$$

3.2. Problem Formulation

HF prediction involves estimating the probability that a patient will develop HF based on a range of clinical and demographic variables. The problem can be formulated as a classification task where the goal is to predict α binary outcome, y, indicating the presence or absence of HF.

Let $\boldsymbol{X}$ represent the feature matrix consisting of n patients, where each patient i is described by a vector of features $\mathbf{x}_i \in R^m$. The goal is to model the probability $P(y_i = 1 | \boldsymbol{x}_i)$ where y_i is a binary indicator of HF for patient i.

To achieve this, we define a predictive model $f(x_i;\theta)$ that outputs the probability of HF given the features x_i and parameters θ :

$$P(y_i = 1 | x_i) = f(x_i; \theta) \quad (6)$$

where $f(x_i;\theta)$ is typically a logistic regression function, neural network, or any other classification model. The model is trained to minimize the loss function, which is often the binary cross-entropy loss for classification problems:

$$L(\theta) = -\frac{1}{n} \sum_{i=1}^{n} [y_i log(f(x_i; \theta)) + (1 - y_i) log (1 - f(x_i; \theta))] \quad (7)$$

In addition to prediction, risk stratification is employed to classify patients into different risk categories based on their predicted probabilities. Let $\hat{p}_i$ denote the predicted probability for patient i. Patients are classified into risk categories C_k (e.g., low, medium, high risk) based on thresholds τ_k:

$$Ck = \{xi \mid \tau k-1 < \hat{p}i \leq \tau k\} \quad (8)$$

The goal is to optimize the model parameters θ such that the predictive accuracy is maximized and risk stratification aligns with clinical outcomes. This formulation addresses the need for accurate prediction and effective risk stratification in HF management.

3.3. Dataset

We used the heart failure clinical records dataset from Kaggle [24], which includes comprehensive patient demographics, clinical measurements, and health conditions. This dataset supports predictive modelling, risk assessment, and clinical research.

Key attributes of the dataset typically include:

1. Age:

(a) Description: Age of the patient in years.

(b) Type: Integer.

2. Blood Pressure:

(a) Description: Systolic and diastolic blood pressure measurements.

(b) Type: Numerical (e.g., systolic in mmHg).

3. Chronic Kidney Disease:

(a) Description: Indicator of chronic kidney disease presence.

(b) Type: Binary (e.g., 0 for No, 1 for Yes).

4. Diabetes:

(a) Description: Indicator of diabetes presence.

(b) Type: Binary (e.g., 0 for No, 1 for Yes).

5. Ejection Fraction:

(a) Description: Percentage of blood pumped out of the heart with each beat.

(b) Type: Numerical (e.g., percentage).

6. Platelets:

(a) Description: Platelet count in blood (e.g., per microliter).

(b) Type: Numerical.

7. Sex:

(a) Description: Gender of the patient.

(b) Type: Categorical (e.g., “Male”, “Female”).

8. Smoking Status:

(a) Description: Indicator of smoking habits.

(b) Type: Binary (e.g., 0 for Non-Smoker, 1 for Smoker).

9. HF Event:

(a) Description: The target variable indicating the occurrence of a HF event.

(b) Type: Binary (e.g., 0 for No event, 1 for HF).

3.4. Proposed Methodology

The proposed methodology for HF prediction integrates predictive analytics with risk stratification to provide a comprehensive approach to identifying and managing HF risk. The methodology is structured into several key phases: data pre-processing, feature engineering, model development, and risk stratification [25].

3.4.1. Data Pre-processing

Data preparation is crucial for ensuring dataset quality and includes the following steps:

- **Data Cleaning:** Managing missing values, removing duplicates, and correcting inconsistencies, with imputation done using statistical methods like mean or median.
- **Normalization:** Scaling numerical features using Min-Max scaling to enhance model performance.
- **Categorical Encoding:** Converting categorical variables into numerical format using label encoding.

3.4.2. Feature Engineering

Feature engineering involves creating and selecting relevant features to enhance model performance:

- **Feature Selection:** Identifying the most significant features using correlation analysis.

- **Feature Creation:** Generating new features that may provide additional insights. For instance, creating interaction terms between different clinical measurements.

3.4.3. Model Development

The model development phase involves training and evaluating predictive models:

- Model Selection: Various ML and DL models, including DTC, RFs, GBMs, LR, XGBC, SVRC, and NNs, are evaluated to build the ensemble network. The ensemble model's performance is assessed using accuracy, precision, recall, and AUC-ROC, as shown in Table.

Table 1. Formation of Ensemble Network

Ensemble Models	Accuracy	Precision	Recall
DTC+RFs	0.80	0.80	0.80
DTC+XGBC+ SVRC	0.85	0.85	0.85
ML+DL ENSEMBLE	0.88	0.88	0.88
RFs+GBMs+LR	0.70	0.70	0.70
NNs+GBMs+LR	0.89	0.89	0.89
NNs+GBMs+ SVRC	0.86	0.86	0.86
DTC+LR+SVRC (Proposed)	**0.91**	**0.91**	**0.94**

From Table 1, the DTC+LR+SVRC ensemble outperforms other models, achieving an accuracy, precision, recall, of 0.91, 0.91 and 0.94 respectively. This model proves most effective at learning complex patterns, making it the chosen ensemble for our network.

- **Hyper-parameter Tuning:** Optimizing model parameters are used to enhance model performance described in Table 2.

Table 2. Hyper-parameter Tuning for Ensemble Models

Ensemble Model	Model Components	Hyper-parameters	Values
DTC+RFs	Decision Tree Classifier (DTC) Random Forests (RFs)	Criterion Max Depth N Estimators Max Features	Gini, Entropy 3, 5, 10 100, 200 Auto, Log2
DTC+XGBC+SVRC	XGBoost Classifier (XGBC) Support Vector Classifier (SVRC)	Learning Rate Max Depth Kernel C	0.01, 0.1 3, 5, 7 Linear, RBF 0.1, 1, 10
RFs+GBMs+LR	Gradient Boosting Machines (GBMs) Logistic Regression (LR)	Learning Rate N Estimators Penalty C	0.01, 0.1 100, 200 L2 0.1, 1, 10

NNs+GBMs+LR	Neural Networks (NNs) Gradient Boosting Machines (GBMs)	Hidden Layers Activation Learning Rate N Estimators	1, 2, 3 ReLU, Sigmoid 0.01, 0.1 100, 200
NNs+GBMs+SVRC	Neural Networks (NNs) Support Vector Classifier (SVRC)	Hidden Layers Activation Kernel C	1, 2, 3 ReLU, Sigmoid Linear, RBF 0.1, 1, 10
DTC+LR+SVRC	Decision Tree Classifier (DTC) Logistic Regression (LR) Support Vector Classifier (SVRC)	Criterion Max Depth Penalty C Kernel C	Gini, Entropy 3,5,10 L2 0.1,1,10 Linear, RBF 0.1,1,10

- **Cross-Validation:** Implementing 5-fold cross-validation to ensure the model generalizes well to unseen data and to avoid overfitting.

3.4.4. Risk Stratification

Risk stratification categorizes patients into different risk levels based on predicted probabilities:

- **Probability Estimation:** The final model predicts the probability of HF for each patient.
- **Threshold Selection:** Defining risk thresholds to classify patients into categories such as low, medium, and high risk. This is done based on clinical guidelines and performance metrics.
- **Risk Categorization:** Assigning patients to risk categories based on the predicted probabilities and thresholds.

3.4.5. Evaluation and Validation

The proposed methodology includes rigorous evaluation and validation to ensure reliability:

- **Model Evaluation:** Assessing model performance using evaluation metrics such as accuracy, precision, recall, F1-score, and AUC-ROC.
- **Performance Comparison:** Comparing the proposed model's performance with existing models to demonstrate improvements.
- **Sensitivity Analysis:** Analysing how changes in input features affect predictions to ensure model robustness.

3.4.6. Implementation and Deployment

The final model is embedded in a clinical decision support system, integrated with EHRs for real-time risk assessment. It features a user-friendly interface for data input and risk evaluation, and is continuously updated to ensure accuracy. This approach enhances HF prediction and management through advanced analytics and risk stratification.

4. Results and Discussion

To evaluate the performance of the proposed model, this study compares its performance with various other ML and DL models. These models include, Gradient Boosting Classifier (GBC) [23], Random Forest (RF) [24], Hybrid Bagging & Boosting Classifier (HBBC) [25], Decision Tree Classifier (DTC) [26], and Support Vector Machines(SVMs) [27].

4.1. Model Evaluation

The evaluation of the proposed model is conducted using the metrics of accuracy, precision, recall, F1-score, and AUC-ROC as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

$$Recall = \frac{TP}{TP+FN} \quad (11)$$

$$F1-Score = 2 \cdot \frac{Precision.Recall}{Precision+Recall} \quad (12)$$

$$AUC-ROC = \int_0^1 TPR\, d(FPR) \quad (13)$$

$$FPR = \frac{FP}{FP+TN} \quad (14)$$

where, TP, TN, FP, FN, TPR, FPR represent True Positives, True Negatives, False Positives, False Negatives, True Positive Rate (Recall), False Positive Rate, respectively.

4.2. Analysis of Heart Failure

Figure 2 compares the mean values of various features between two groups: those who experienced a death event and those who did not. The heatmap make it easy to visually compare the average values of features between the two groups, using a color gradient where one color represents higher values and another represents lower values.

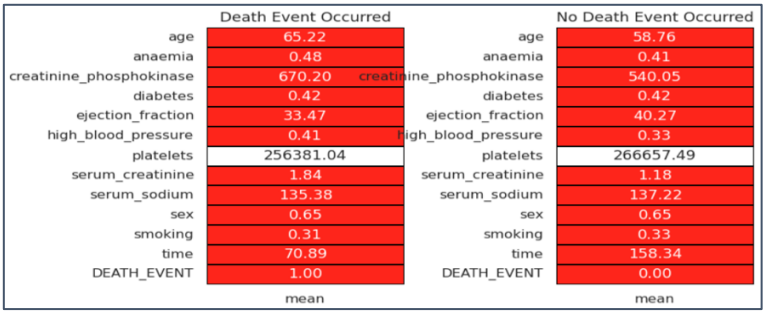


Figure 2. Death Occurrence due to Heart Failure

Figure 3. and Figure 4. depict the distribution of different categorical and numerical features of the used dataset.

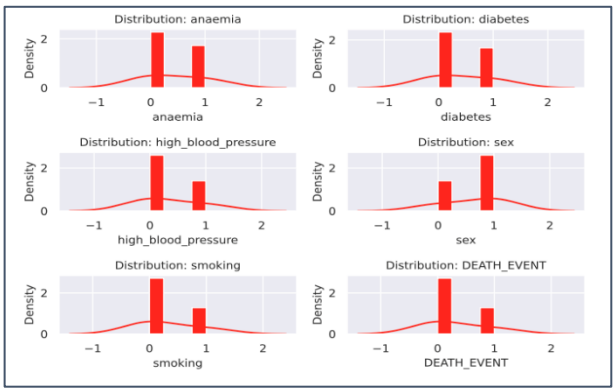


Figure 3. Distribution of Different Categorical Features

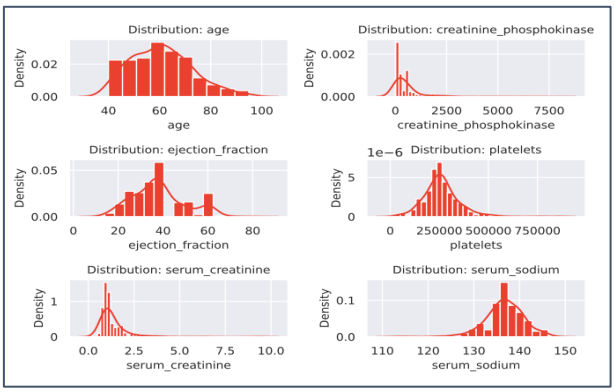


Figure 4. Distribution of Different Numerical Features

Figure 5 depicts with two subplots: a pie chart and a count plot. The pie chart shows the percentage distribution of death events and non-death events, while the count plot displays the counts of each category with customized bar widths and labels.

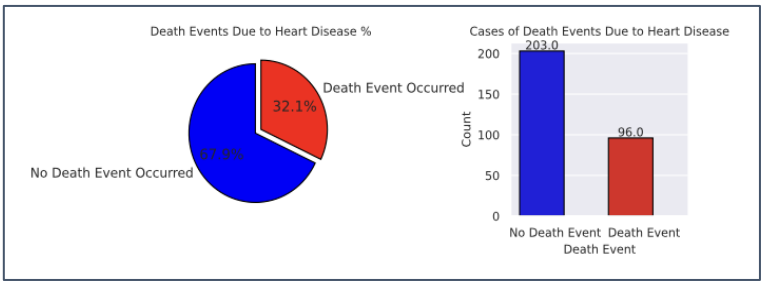


Figure 5. Pie Chart and Count Plot of Heart Failure

Figure 6 displays a heatmap that illustrates the correlations between numerical features in the dataset, highlighting both the strength and direction of these correlations. The heatmap includes annotated correlation coefficients to offer precise values for each correlation.

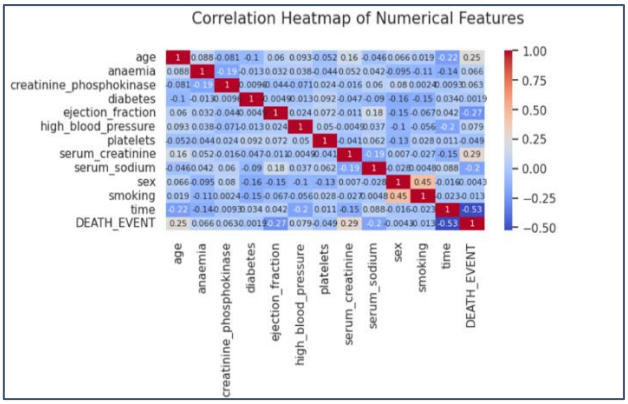


Figure 6. Heatmap of the Used Dataset of Heart Failure

Figure 7 showcases the results of the Chi-Squared and ANOVA tests, respectively.

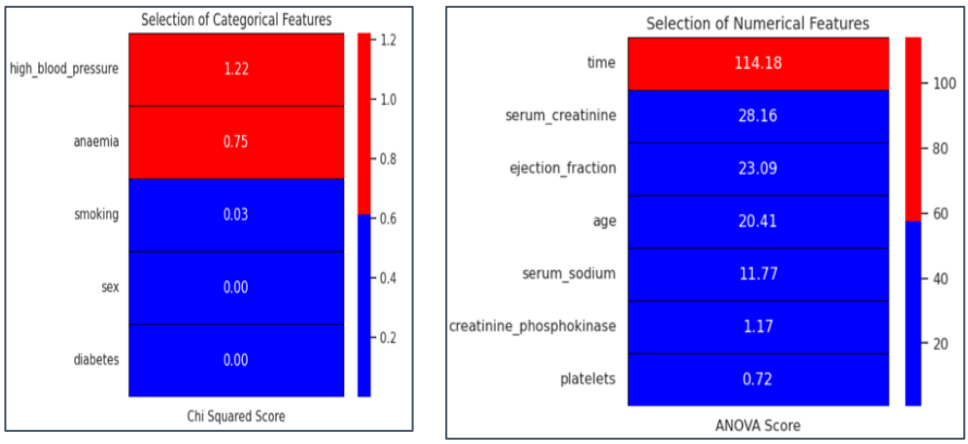
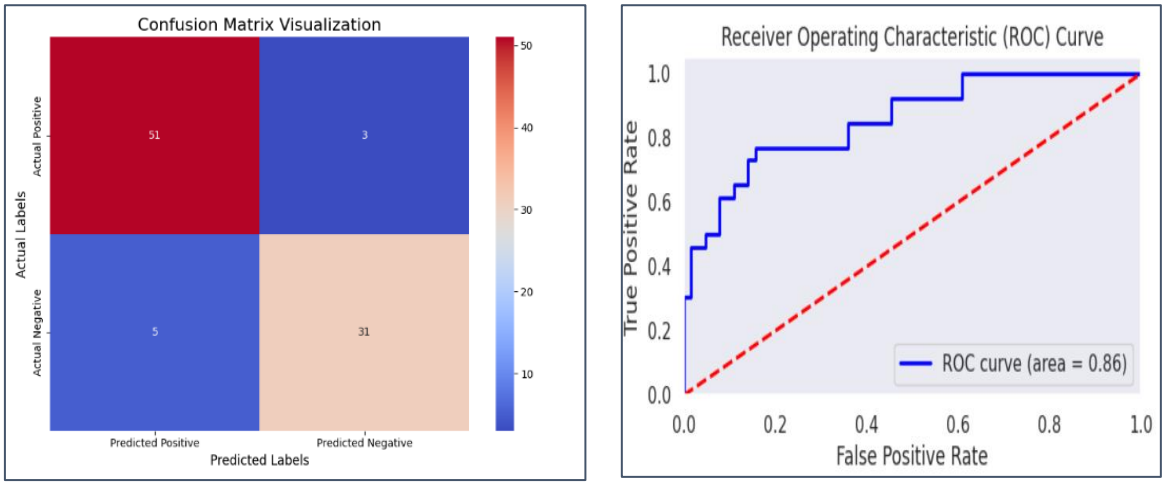


Figure 7 (a). Chi Squared Test (b). ANOVA Score Test

4.3. HF Prediction using Proposed Model

HF prediction with ensembling integrates multiple ML models to boost accuracy and robustness. After preparing the data and selecting features, models such as Logistic Regression, SVC, and Decision Tree are combined using a Voting Classifier. The ensemble is trained and tested, with performance assessed through metrics like accuracy and classification reports, enhancing prediction reliability.

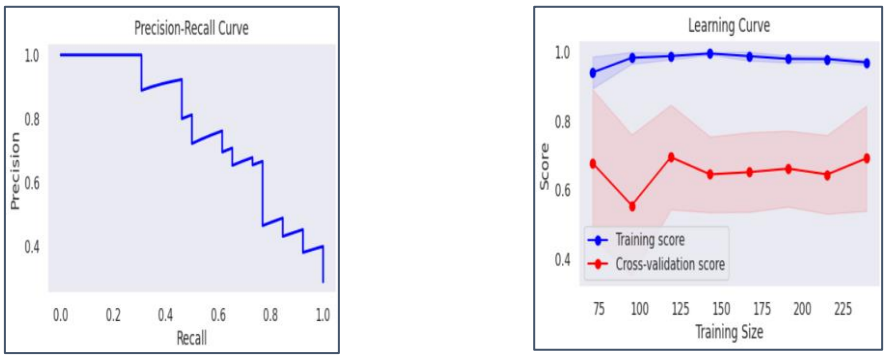
Figure 8(a) depicts the confusion matrix of the proposed model.



(a) (b)

Figure 8 (a). Confusion Matrix of Proposed Model (b). ROC Curve of Proposed Model

Figure 8(b), 9(a), and 9(b) illustrate the ROC Curve, Precision-Recall Curve, and the Learning Curves of the proposed model.



(a) (b)

Figure 9 (a). Precision-Recall Curve of Proposed Model (b). Learning Curves of Model

4.4. Loss of the Proposed Model

Figure 10 depicts the loss of the proposed model.

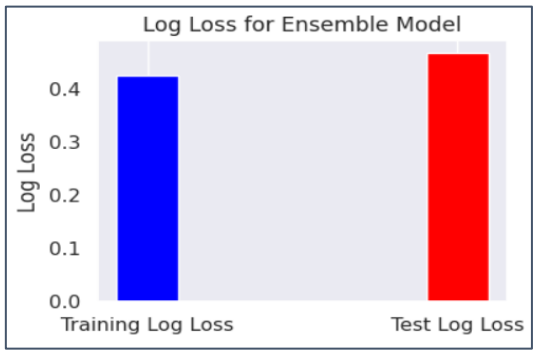


Figure 10. Loss of the Proposed Model

4.5. Comparison Results

Table 3 shows a comparison of prediction performance among all the compared state-of-the-art models based on accuracy, precision, recall and F1-score.

Table 3 presents a comparative analysis of various state-of-the-art models, highlighting the superior performance of the proposed model. It achieves the highest scores across all metrics: accuracy (0.91), precision (0.91), recall (0.94) and F1-score (0.92).

Table 3. Comparison of Prediction Performance among State-of-the-Art Models

Model	Precision	Recall	F1-score	Accuracy(%)
LR [26]	0.857	0.853	0.854	85.3
KNN [26]	0.904	0.902	0.902	90.2
GBC [26]	0.875	0.875	0.875	87.5
RF [27]	0.852	0.906	0.878	86.9
DTC [28]	0.895	0.816	0.854	86.37
MLP [28]	0.887	0.848	0.900	87.28
XGB [29]	0.882	0.882	0.882	88.19
DTC+LR+SVRC (Proposed)	**0.910**	**0.944**	**0.924**	**91.11**

The Logistic Regression (LR) performs the weakest in accuracy. Overall, the model demonstrates greater robustness and reliability for predicting outcomes, showing superior performance in capturing and predicting complex patterns compared to other state-of-the-art models.

5. Conclusion

The proposed model represents a major step forward in heart failure (HF) prediction, utilizing ensemble learning to combine multiple machine learning algorithms, thereby improving both accuracy and robustness. Its exceptional performance across key metrics accuracy, precision, recall and F1-score sets a new standard in predictive analytics and risk stratification for cardiovascular health. The successful implementation of the proposed model highlights the power of ensemble learning in medical data analysis, offering a reliable tool for early detection and intervention, which can lead to better patient outcomes and more effective heart disease management.

Future advancements could further enhance the model's capabilities. Exploring more sophisticated ensemble techniques, such as stacking and blending, may increase its predictive power. Additionally, improving the model's interpretability and explainability will help healthcare professionals understand and trust its predictions, promoting broader clinical adoption. Testing the model's scalability and generalizability across diverse populations and healthcare systems is also crucial to ensure its applicability in various settings. Moreover, deploying the proposed model in real-world clinical environments and integrating it with electronic health record (EHR) systems could automate heart failure risk stratification, streamlining patient care and optimizing healthcare resources.

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