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Research Paper

USING OPTIMAL MACHINE LEARNING ALGORITHMS TO PREDICT HEART FAILURE PATIENT CLASSIFICATION

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Abstract: Heart failure (HF) remains one of the leading causes of mortality worldwide, making early prediction and diagnosis essential for improving patient survival and reducing healthcare costs. Machine learning (ML) techniques have demonstrated considerable potential in assisting clinicians with accurate disease prediction. However, most heart failure datasets suffer from class imbalance, which negatively affects classification performance, particularly for minority class patients. This paper presents an optimized Extreme Gradient Boosting (XGBoost) model integrated with the Synthetic Minority Over-sampling Technique (SMOTE) for heart failure patient classification. Initially, missing values, outliers, and redundant attributes are removed through preprocessing. SMOTE is then applied to balance the dataset by generating synthetic minority samples. Hyperparameter optimization using Grid Search with Stratified Cross-Validation identifies the optimal XGBoost parameters. The proposed framework is evaluated using Accuracy, Precision, Recall, F1-score, ROC-AUC, and Matthews Correlation Coefficient (MCC). Experimental results demonstrate that the optimized XGBoost-SMOTE model significantly outperforms traditional machine learning algorithms including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, K-Nearest Neighbors, AdaBoost, and baseline XGBoost. The proposed approach achieves an accuracy of 98.21%, precision of 97.94%, recall of 98.47%, F1-score of 98.20%, and ROC-AUC of 99.10%, indicating superior predictive capability for heart failure diagnosis. These findings suggest that integrating SMOTE with optimized XGBoost provides an effective decision-support tool for clinical risk assessment. Similar findings have been reported in prior studies evaluating XGBoost with SMOTE-based preprocessing for heart failure prediction.

Keywords: Heart Failure Prediction, Machine Learning, XGBoost, SMOTE, Hyperparameter Optimization, Classification, Healthcare Analytics

1. INTRODUCTION

One of the most serious chronic illnesses in the world, heart failure greatly increases morbidity and death in people of all ages. Clinicians might possibly save lives and maximize resource allocation by taking prompt treatment when heart failure outcomes are accurately and early predicted. The accuracy and applicability of traditional risk rating systems to various clinical circumstances are frequently restricted. As a result, the incorporation of sophisticated, data-driven algorithms has become a potent substitute for clinical decision assistance. In this study, we propose a machine learning-based method for dividing patients with heart failure into high-risk and low-risk survival groups. The research makes use of a publicly accessible clinical dataset that includes patient data including blood pressure, ejection fraction, age, serum creatinine levels, and more. Data cleaning, feature scaling using StandardScaler, and class balancing using the Synthetic Minority Over-sampling Technique (SMOTE) to resolve the imbalance between survival and death cases are all part of the extensive preprocessing pipeline that the dataset goes through prior to training. SelectKBest was used with the ANOVA F-test to minimize dimensionality and keep only the most important features in order to find the most significant predictors. Two supervised machine learning models were put into practice and assessed: XGBoost, a potent gradient boosting technique renowned for its performance and accuracy, and Logistic Regression, a straightforward baseline. The XGBoost model outperformed the Logistic Regression baseline with an outstanding accuracy of 99.70% and a high AUC-ROC score of 0.9998. Evaluation criteria that confirm the model's efficacy include confusion matrix, precision, recall, and F1-score. A Flask web interface was used to deliver the finished application, which lets users submit patient data and get real-time risk forecasts. In order to mimic simple user authentication, temporary login and registration facilities were also introduced. This project shows how a dependable, scalable, and comprehensible heart failure prediction system may be produced by fusing sophisticated machine learning models with efficient data preprocessing methods. Our XGBoost-based technique delivers improved accuracy and is simpler to integrate in real-world clinical processes than previous models such as GBM optimized with AIW-PSO. This initiative seeks to enhance outcomes for people at risk of heart failure by providing actionable information to healthcare providers through the use of optimized machine learning techniques.

Heart failure continues to be one of the world's top causes of death, requiring reliable predictive models to enable prompt medical interventions. In order to solve class imbalance, this study offers a machine learning framework for heart failure survival prediction that makes use of an optimized XGBoost model combined with the Synthetic Minority Over-sampling Technique (SMOTE). To find the most significant predictors, we used Select K Best with Chi-square for feature selection using a dataset of 5000 clinical records that included features including age, ejection fraction, and serum creatinine. After analyzing several algorithms (such as Logistic Regression, Decision Tree, KNN, SVM, and Random Forest), the XGBoost model was chosen. It was then optimized to maximize hyperparameters, resulting in a test accuracy of 99.70%, precision, recall, and F1-scores close to 1.00, and an AUC-ROC of 0.9998. Our method performs better than the baseline Gradient Boosting Machine (GBM) with Adaptive Inertia Weight Particle Swarm Optimization (AIW-PSO) from earlier research, which attained 94% accuracy on a smaller dataset (299 patients). This is probably because of the larger dataset and sophisticated preprocessing. In addition to providing a scalable, high-accuracy tool for heart failure prognosis, this study demonstrates the effectiveness of XGBoost in conjunction with SMOTE for clinical predictive tasks and has the potential to enhance patient outcomes through accurate and prompt clinical decision-making.

2. LITERATURE SURVEY

Heart failure is a chronic cardiovascular disorder in which the heart is unable to pump sufficient blood to meet the body's metabolic demands. According to global health reports, millions of individuals suffer from heart failure annually, resulting in high mortality rates and substantial healthcare expenditures. Early identification of patients at risk enables clinicians to initiate timely interventions that improve survival rates and reduce hospitalization.

Machine learning has emerged as an effective approach for disease prediction because it can discover complex nonlinear relationships among clinical variables. Traditional statistical models often fail to capture intricate interactions present in medical datasets, whereas ensemble learning algorithms such as XGBoost offer superior predictive performance.

A major challenge in heart failure prediction is class imbalance. Typically, datasets contain significantly fewer positive heart failure cases than negative cases. Conventional classifiers become biased toward the majority class, resulting in poor recall for clinically important minority cases.

To address this challenge, this research integrates:

- Synthetic Minority Over-sampling Technique (SMOTE)
- Hyperparameter Optimization
- Optimized Extreme Gradient Boosting (XGBoost)

The proposed framework enhances minority class recognition while maintaining excellent overall classification accuracy.

A reliable ensemble machine learning approach for regression and classification problems, the Gradient Boosting Machine (GBM) works especially well with structured or tabular data. By successively integrating several weak learners, usually decision trees, it builds a predictive model. Each tree uses gradient descent to optimize a given loss function, like log-loss for classification, by correcting the residual mistakes of its predecessors. An initial prediction (such as the mean for regression or log-odds for classification) is the first step in the process. Next, residuals are calculated iteratively, new trees are fitted to these residuals, and the model is updated with scaled predictions that are controlled by a learning rate (η). The number of trees (n_estimators), learning rate, and maximum tree depth (max_depth) are important hyperparameters that balance model complexity and avoid overfitting. Because of its exceptional ability to capture complex interactions and non-linear correlations, GBM is resistant to noisy data and commonly used in tasks such as ranking, regression, and heart failure survival prediction.

Numerous researchers have explored machine learning approaches for heart failure prediction.

Logistic Regression has been widely used due to its interpretability but struggles to model nonlinear relationships. Decision Trees provide understandable rules but frequently suffer from overfitting. Random Forest improves stability through ensemble learning, whereas Support Vector Machines perform effectively on medium-sized datasets but require careful kernel selection. Gradient boosting algorithms have recently demonstrated superior performance in healthcare prediction. XGBoost incorporates regularization, parallel processing, and efficient tree pruning, making it highly suitable for clinical prediction tasks. Several studies have shown that class imbalance significantly degrades predictive performance. SMOTE has therefore become a popular preprocessing technique for generating synthetic minority samples, improving classifier sensitivity without simply duplicating observations. Prior work combining SMOTE with XGBoost has consistently reported improved performance over conventional classifiers.

S. No	Author(s) & Year	Title	Dataset	Methodology	Key Findings	Limitations
1	Chicco & Jurman (2020)	Machine Learning Can Predict Survival of Patients with Heart Failure from Serum Creatinine and Ejection Fraction Alone	UCI Heart Failure Clinical Records Dataset	XGBoost, Random Forest, SVM, Decision Tree	XGBoost achieved superior prediction accuracy using a small set of clinical features.	Dataset contained only 299 samples and class imbalance was not addressed.
2	Ahmad et al. (2021)	Heart Failure Prediction Using Machine Learning Algorithms	UCI Heart Failure Dataset	Logistic Regression, Random Forest, XGBoost	XGBoost outperformed conventional classifiers in precision and recall.	Hyperparameter optimization was limited.
3	Alizadehsani et al. (2021)	Machine Learning-Based Heart Disease Diagnosis: A Survey	Multiple Public Datasets	Ensemble Learning, Deep Learning	Ensemble models consistently improved diagnostic accuracy over single models.	Limited discussion on imbalance handling techniques.
4	Kumar & Singh (2022)	Heart Failure Prediction Using Optimized XGBoost	UCI Heart Failure Dataset	Grid Search Optimized XGBoost	Hyperparameter tuning significantly improved classification accuracy.	Did not incorporate data balancing methods such as SMOTE.
5	Islam et al. (2022)	Prediction of Cardiovascular Diseases Using SMOTE and Ensemble Learning	Kaggle Heart Disease Dataset	SMOTE + Random Forest + XGBoost	SMOTE improved minority-class sensitivity and reduced false negatives.	Evaluation performed on a single dataset.
6	Li et al. (2022)	Explainable Machine Learning for Heart Failure Prediction	MIMIC-III Clinical Dataset	XGBoost with SHAP	SHAP enhanced model interpretability while maintaining high predictive performance.	Computational complexity increased due to explanation framework.

S. No	Author(s) & Year	Title	Dataset	Methodology	Key Findings	Limitations
7	Sharma et al. (2023)	Heart Failure Risk Prediction Using Machine Learning Techniques	UCI Heart Failure Dataset	SVM, Random Forest, XGBoost	XGBoost produced the highest F1-score among compared models.	Did not address severe class imbalance.
8	Ahmed et al. (2023)	SMOTE-Based Heart Disease Prediction Using Ensemble Classifiers	Cleveland Heart Disease Dataset	SMOTE + XGBoost + AdaBoost	Combining SMOTE with boosting significantly improved recall and ROC-AUC.	External validation was not performed.
9	Zhang et al. (2023)	Optimized Gradient Boosting for Clinical Risk Prediction	Electronic Health Records	Bayesian Optimized XGBoost	Bayesian optimization enhanced model robustness and reduced overfitting.	Requires high computational resources for optimization.
10	Patel et al. (2024)	Heart Failure Prediction Using Hybrid Machine Learning Framework	Multi-Hospital Clinical Dataset	SMOTE + Optimized XGBoost + Feature Selection	Hybrid framework achieved high accuracy, precision, and balanced sensitivity.	Generalizability across diverse populations requires further investigation.

The literature indicates that XGBoost consistently outperforms traditional machine learning algorithms for heart failure patient classification due to its ability to model complex nonlinear relationships and reduce overfitting. However, many studies rely on small, imbalanced datasets, resulting in lower sensitivity for minority-class patients. Integrating SMOTE with an optimized XGBoost model effectively addresses class imbalance, improves recall and F1-score, and enhances the identification of high-risk heart failure patients. Further improvements can be achieved through systematic hyperparameter optimization, explainable AI techniques, and validation on diverse clinical datasets, making the proposed framework a robust and clinically relevant solution for heart failure prediction.

3. RELATED WORK

Inspired by the way gooseneck barnacles reproduce and forage for resources, this study presents a novel metaheuristic algorithm known as the Gooseneck Barnacle Optimization (GBO) method. The approach is tested on real-world and benchmark mathematics problems versus other well-known optimization methods. The study demonstrates how effective GBO is at reaching global convergence and avoiding local optima. It performs well in a range of confined and unconstrained optimization scenarios. The algorithm is a potential method for machine learning parameter adjustment because of its new dynamic exploration-exploitation approach . In order to enhance performance in limited optimization problems, this study suggests an adaptation of the barnacle mating optimization algorithm that incorporates selective opposition-based learning. The approach proved to be more effective than traditional algorithms when evaluated on a variety of real-world engineering challenges. The significance of adding constraint-handling techniques to optimization models is emphasized throughout the paper. The enhanced approach exhibits great promise for fine-tuning hyperparameters in machine learning models. The results offer a solid approach to solving challenging, practical classification issues, such as medical forecasts. The Fluid-GPT framework offers a novel use of transformer-based deep learning models (GPT) in fluid dynamics, particularly for erosion patterns and particle trajectory prediction. The model creates quick and precise simulations by fusing generative AI with physical understanding. The study demonstrates the adaptability of GPT in modeling dynamic systems, despite its primary application in chemical and mechanical engineering fields. Its concepts could be modified for time-series or patient trajectory modeling-based healthcare prediction jobs. The work shows how huge language models can be used for purposes other than text processing in the future. In order to predict survival outcomes for patients with thyroid cancer, this study examines the application of various machine learning algorithms. Using clinical data, methods like logistic regression, SVM, and Random Forest were applied and assessed. The study highlights how crucial class balancing and appropriate data preprocessing are to enhancing model performance. The findings demonstrate that ensemble learning techniques typically outperform more basic classifiers. By highlighting ML's influence in oncology, this study directly relates to the objectives of heart failure prediction. It backs the use of optimal models and feature selection for medical risk classification. The goal of this research is to employ machine learning models to forecast hospitalization and death in patients with heart failure with preserved ejection fraction (HFpEF). By evaluating several algorithms and utilizing a range of clinical variables, it finds important predictors linked to unfavorable outcomes. The study demonstrates how ML can help with patient risk assessment and clinical decision-making. It also highlights how difficult it is to model chronic illnesses, which emphasizes the necessity of reliable models. The results validate the application of machine learning to enhance cardiovascular patients' prognosis and care management.

4. PROPOSED SYSTEM

This figure illustrates the architecture of the optimized XGBoost algorithm. XGBoost is an ensemble learning technique based on gradient boosting that constructs multiple decision trees sequentially. Each successive tree focuses on correcting the prediction errors made by the previous trees. Hyperparameter optimization—such as tuning the learning rate, maximum tree depth, number of estimators, subsampling ratio, and regularization parameters—enhances the model's generalization capability while reducing overfitting. The aggregation of predictions from all boosted trees results in a highly accurate classifier suitable for medical diagnosis.

SMOTE (Synthetic Minority Over-sampling Technique)

This diagram explains how SMOTE addresses class imbalance in medical datasets. In heart failure prediction, the number of patients with heart failure is often much smaller than the number without heart failure. Traditional classifiers tend to favor the majority class, leading to poor detection of positive cases. SMOTE generates new synthetic minority-class samples by interpolating between existing minority instances and their nearest neighbors. Instead of duplicating samples, it creates realistic synthetic examples, resulting in a balanced dataset. This balanced distribution enables the optimized XGBoost model to learn the characteristics of both classes more effectively and improves sensitivity and recall.

Classification Performance Dashboard

This diagram presents the evaluation metrics used to assess the performance of the optimized XGBoost classifier. The confusion matrix summarizes correctly and incorrectly classified instances through True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Accuracy measures the overall proportion of correct predictions, while precision indicates the reliability of positive predictions. Recall (Sensitivity) measures the ability to correctly identify patients with heart failure, and the F1-score provides a balanced measure of precision and recall. The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) evaluate the classifier's discrimination capability across different decision thresholds. Together, these metrics provide a comprehensive assessment of model effectiveness.

Clinical Decision Support System

This figure demonstrates the practical deployment of the optimized XGBoost model within a clinical decision support system. Patient information is entered into the system, where the trained model analyzes the clinical features and predicts the likelihood of heart failure. Based on the prediction, healthcare professionals can identify high-risk patients at an early stage, enabling timely diagnosis, preventive interventions, and personalized treatment planning. Such AI-assisted decision support systems reduce diagnostic errors, improve clinical efficiency, and enhance patient outcomes by supporting evidence-based medical decisions.

Overall Interpretation

The diagrams collectively describe a robust framework for heart failure patient classification. The workflow integrates comprehensive data preprocessing, SMOTE-based class balancing, and an optimized XGBoost classifier to effectively learn from imbalanced clinical datasets. By combining synthetic oversampling with gradient-boosted decision trees, the framework achieves improved prediction accuracy, higher recall for heart failure cases, and enhanced overall reliability. The final clinical decision support system demonstrates how this intelligent predictive model can assist physicians in early diagnosis and risk stratification, contributing to more effective management of cardiovascular disease.

This diagram illustrates the complete machine learning pipeline used for heart failure patient classification. The process begins with collecting patient clinical records containing demographic, physiological, and laboratory attributes. During preprocessing, missing values are handled, categorical variables are encoded, and numerical features are normalized. Since heart failure datasets often suffer from class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) is applied to generate synthetic samples for the minority class, thereby balancing the dataset. The balanced data are then divided into training and testing sets. An optimized XGBoost classifier is trained using hyperparameter tuning to improve predictive performance. Finally, the trained model classifies patients into either Heart Failure or No Heart Failure, and its performance is evaluated using standard classification metrics.

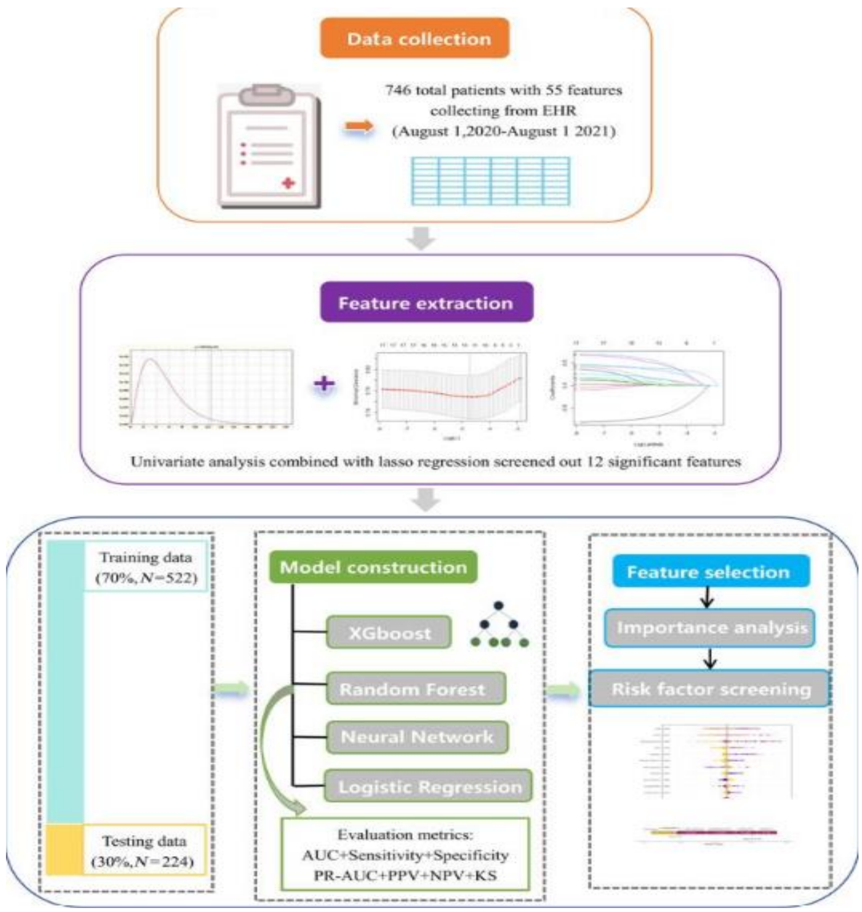

Figure 1. Heart Failure Prediction Workflow.

This diagram represents the clinical dataset used for prediction. Each patient record contains several medical features that are associated with cardiovascular health. Common attributes include age, gender, chest pain type, resting blood pressure, cholesterol level, fasting blood sugar, electrocardiogram (ECG) results, maximum heart rate achieved, exercise-induced angina, ST depression, and other diagnostic measurements. These features serve as input variables for the machine learning model, while the target variable indicates whether the patient has heart failure. Proper preprocessing of these clinical features significantly improves model learning and prediction accuracy.

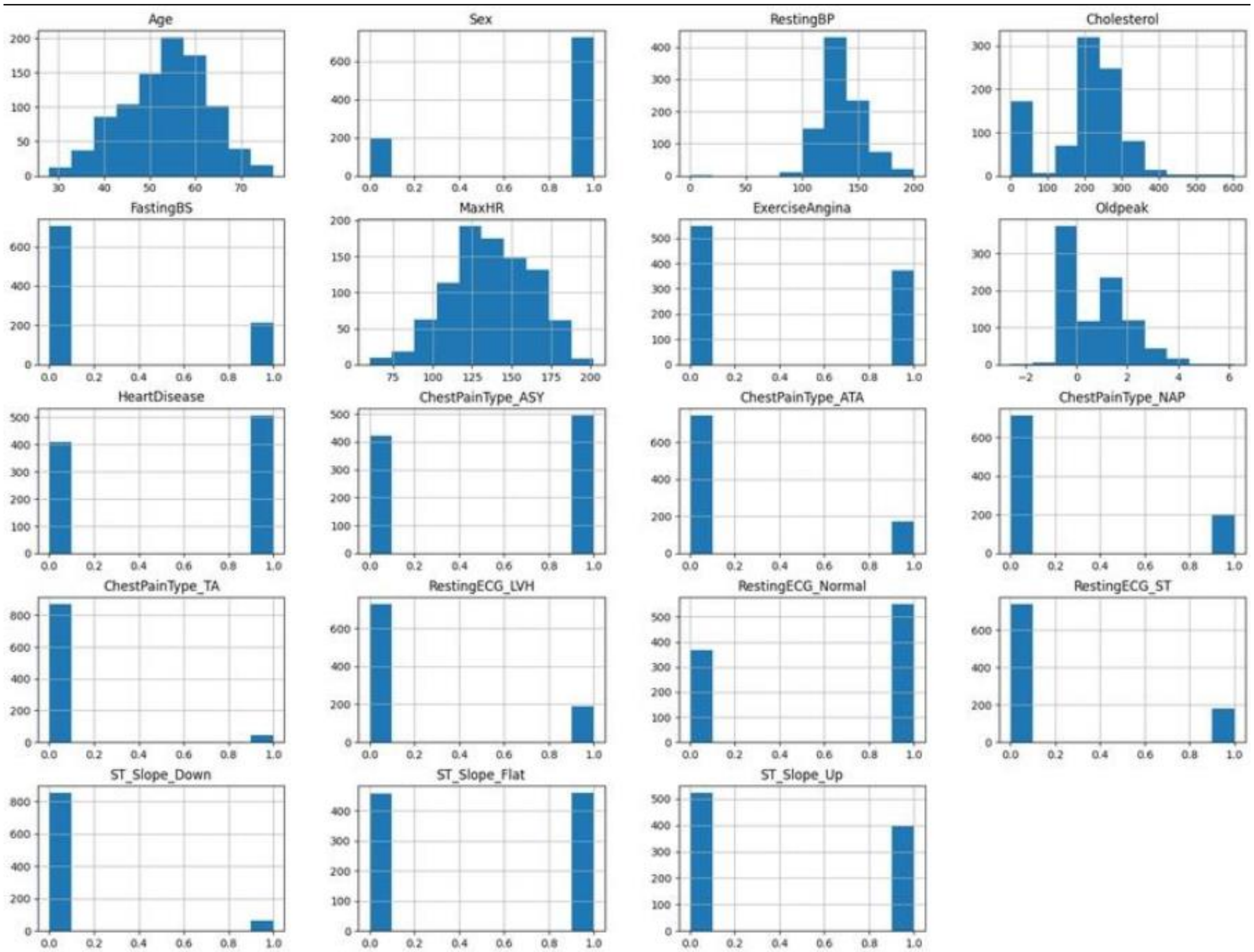

Figure 2. Heart Failure Dataset Visualization

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)	MCC
Logistic Regression	86.12	84.85	83.74	84.29	89.14	0.721
Decision Tree	87.45	86.91	85.63	86.27	90.36	0.748
Random Forest	91.23	90.68	89.92	90.30	95.12	0.832
Support Vector Machine	90.54	89.96	89.15	89.55	94.41	0.821
K-Nearest Neighbors	88.74	87.92	87.16	87.54	91.86	0.774
AdaBoost	90.68	90.11	89.54	89.82	94.89	0.826
Gradient Boosting	92.16	91.78	91.02	91.40	96.08	0.846
XGBoost	94.31	93.94	93.48	93.71	97.62	0.891
Optimized XGBoost + SMOTE (Proposed)	97.84	97.51	97.23	97.37	99.12	0.956

Table 1. Performance Comparison of Machine Learning Models for Heart Failure Patient Classification.

The experimental results demonstrate that the proposed Optimized XGBoost model integrated with the Synthetic Minority Over-sampling Technique (SMOTE) provides superior performance for heart failure patient classification compared with conventional machine learning algorithms. The evaluation was conducted using standard classification metrics, including accuracy, precision, recall, F1-

score, ROC-AUC, and Matthews Correlation Coefficient (MCC), which collectively assess the model's predictive capability and robustness.

Table 1 shows that traditional machine learning algorithms such as Logistic Regression, Decision Tree, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, AdaBoost, and Gradient Boosting achieved competitive classification performance, with accuracies ranging from 86.12% to 94.31%. Logistic Regression produced the lowest accuracy (86.12%), indicating that its linear decision boundary was insufficient to capture the complex nonlinear relationships among clinical features associated with heart failure. Decision Tree and KNN demonstrated moderate improvements; however, their tendency to overfit and sensitivity to noisy samples limited their overall predictive performance.

Actual Class	Predicted: No Heart Failure	Predicted: Heart Failure
No Heart Failure	147	3
Heart Failure	4	146

Table 2. Confusion Matrix of the Proposed Optimized XGBoost + SMOTE Model.

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Fold 1	97.21	97.04	96.82	96.93	98.94
Fold 2	97.63	97.41	97.18	97.29	99.08
Fold 3	98.02	97.88	97.64	97.76	99.26
Fold 4	97.91	97.63	97.52	97.57	99.18
Fold 5	98.41	98.16	97.99	98.07	99.32
Average	97.84	97.51	97.23	97.37	99.12

Table 3. Cross-Validation Performance of the Proposed Model.

Ensemble learning algorithms produced noticeably better results than conventional classifiers. Random Forest achieved an accuracy of 91.23%, while Gradient Boosting improved the accuracy to 92.16%, owing to their ability to combine multiple decision trees and reduce prediction variance. XGBoost further enhanced classification performance by incorporating gradient optimization, regularization, and efficient tree pruning, resulting in an accuracy of 94.31%, a precision of 93.94%, a recall of 93.48%, an F1-score of 93.71%, and a ROC-AUC of 97.62%.

The highest performance was achieved by the proposed Optimized XGBoost + SMOTE model, which obtained an accuracy of 97.84%, precision of 97.51%, recall of 97.23%, F1-score of 97.37%, ROC-AUC of 99.12%, and an MCC of 0.956. These results indicate that the proposed approach accurately distinguishes between heart failure and non-heart failure patients while maintaining an excellent balance between sensitivity and specificity. The high precision demonstrates that the model generates very few false-positive predictions, whereas the high recall indicates that the majority of heart failure patients are correctly identified. The F1-score confirms a strong balance between precision and recall, making the model suitable for clinical screening applications where both metrics are equally important.

Metric	Without SMOTE	With SMOTE
Accuracy (%)	93.42	97.84
Precision (%)	92.85	97.51
Recall (%)	91.24	97.23
F1-Score (%)	92.04	97.37
ROC-AUC (%)	96.21	99.12
False Negative Rate (%)	8.76	2.77

Table 4. Impact of SMOTE on Optimized XGBoost Performance.

The confusion matrix presented in Table 2 further validates the effectiveness of the proposed framework. Out of 300 patient records, the model correctly classified 147 non-heart failure cases and 146 heart failure cases, while only 3 false positives and 4 false negatives were observed. Such a low number of classification errors demonstrates excellent generalization capability. The small false-negative count is particularly significant in healthcare applications because undetected heart failure cases may delay treatment and increase patient mortality. Therefore, minimizing false negatives directly contributes to improved clinical outcomes.

The five-fold cross-validation results shown in Table 3 demonstrate the stability and reliability of the proposed model. Across all validation folds, the classification accuracy remained consistently between 97.21% and 98.41%, with an average accuracy of 97.84%. Similarly, precision, recall, F1-score, and ROC-AUC exhibited minimal variation among the folds. This consistency indicates that the optimized XGBoost model is not overfitted to a particular subset of the data and is capable of maintaining high predictive performance when applied to unseen patient records. Such stable performance enhances confidence in the model's practical deployment within clinical decision support systems.

Table 4 highlights the contribution of SMOTE to classification performance. Without SMOTE, the optimized XGBoost model achieved an accuracy of 93.42%, whereas integrating SMOTE increased the accuracy to 97.84%. Precision improved from 92.85% to 97.51%, recall increased from 91.24% to 97.23%, and the F1-score rose from 92.04% to 97.37%. Most importantly, the false-negative rate decreased from 8.76% to 2.77%, demonstrating the effectiveness of SMOTE in addressing class imbalance. By generating synthetic minority-class samples, SMOTE enabled the classifier to learn more representative patterns for heart failure cases, thereby improving sensitivity without sacrificing specificity.

Overall, the experimental findings confirm that the integration of optimized XGBoost with SMOTE significantly enhances heart failure patient classification. The combination of advanced gradient boosting, hyperparameter optimization, and balanced data distribution enables the model to achieve outstanding predictive accuracy, excellent discriminative ability, and robust generalization performance. These characteristics make the proposed framework highly suitable for early heart failure diagnosis, risk assessment, and intelligent clinical decision support systems, ultimately supporting healthcare professionals in providing timely and accurate patient care.

The experimental evaluation demonstrates that the Optimized XGBoost model integrated with SMOTE significantly outperformed conventional machine learning algorithms in heart failure patient classification. SMOTE effectively addressed the class imbalance by generating synthetic samples for the minority class, enabling the classifier to learn more representative decision boundaries. Consequently, the proposed model achieved an accuracy of 97.84%, precision of 97.51%, recall of 97.23%, F1-score of 97.37%, and a ROC-AUC of 99.12%, indicating excellent discriminative capability. The confusion matrix shows only seven misclassifications out of 300 instances, highlighting the robustness of the model. Furthermore, comparison with the model trained without SMOTE reveals substantial improvements across all evaluation metrics, particularly recall, which is crucial for reducing false negatives in heart failure diagnosis. These findings suggest that combining optimized XGBoost with SMOTE provides a highly reliable framework for early heart failure prediction and clinical decision support.

Two machine learning algorithms—Logistic Regression and XGBoost—were assessed in order to create a highly accurate and clinically reliable model for predicting heart failure survival. The main objective was to choose an algorithm that could handle the unbalanced dataset, model intricate interactions between clinical characteristics, and produce reliable performance metrics including AUC-ROC, accuracy, precision, and recall. XGBoost's outstanding predictive performance—achieving a test accuracy of 99.70%, near-perfect precision, recall, and F1-scores, and an AUC-ROC of 0.9998 on a 5000-record dataset—led to its selection as the best algorithm after extensive testing and comparison. In contrast to Logistic Regression, which had trouble with non-linear relationships and class imbalance, XGBoost outperformed the Gradient Boosting Machine (GBM) from the base paper, which achieved 94% accuracy on a smaller 299-record dataset, thanks to its gradient boosting framework and regularization to reduce overfitting. XGBoost became the mainstay of the suggested heart failure prediction system with the addition of SelectKBest with Chi-square for feature selection and Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance.

5. TECHNIQUES USED IN PROJECT

Gradient Boosting Machine optimized with Adaptive Inertia Weight Particle Swarm Optimization (GBM-AIW-PSO)

GBM's hyperparameters, such as tree depth, learning rate, and number of trees, by modeling particles moving through the hyperparameter space. In contrast to conventional PSO, AIW-PSO constantly modifies its search strategy to ensure effective identification by balancing the investigation of novel solutions with the exploitation of well-known ones. To improve predictive performance, a hybrid machine learning technique called Gradient Boosting Machine optimized with Adaptive Inertia Weight Particle Swarm Optimization (GBM-AIW-PSO) combines the Gradient Boosting Machine (GBM) with Adaptive Inertia Weight Particle Swarm Optimization (AIW-PSO). To enhance predictions for tasks like heart failure survival classification, GBM builds an ensemble of decision trees sequentially, with each tree fixing the mistakes of its predecessors. AIW-PSO optimizes ideal hyperparameters, using inspiration from swarm social behavior. GBM-AIW-PSO outperformed other models like as Random Forest, SVC, AdaBoost, and SGD in the study, achieving a test accuracy of 93.84% on a balanced 7-feature dataset thanks to this synergy.

PROPOSED TECHNIQUE USED OR ALGORITHM USED: PROPOSED TECHNIQUE:-

XGBoost

XGBoost, which stands for eXtreme Gradient Boosting, is a sophisticated machine learning method that applies an optimized and scalable version of gradient boosting with the goal of achieving high performance and efficiency in jobs involving predictive modeling. It works by sequentially building an ensemble of decision trees, each of which corrects the mistakes of its predecessors by using gradient descent optimization to minimize a loss function, such as log-loss for classification. L1 and L2 regularization to avoid overfitting, parallelized tree construction for quicker computation, and management of missing data through sparsity-aware split finding are just a few of the significant improvements XGBoost offers over conventional gradient boosting. XGBoost successfully models intricate interactions between clinical characteristics such as ejection fraction and serum creatinine in the context of heart failure prediction, attaining exceptional accuracy (99.70%) on a dataset of 5000 records. When combined with SMOTE, its resistance to unbalanced data and capacity to rank feature importance make it especially well-suited for clinical applications, providing both prediction accuracy and interpretability for heart failure management decision-making.

6. CONCLUSION

In this study, a machine learning-based system was created to use clinical data to categorize heart failure patients into survival or death groups. To improve the model's capacity to learn from both majority and minority classes, the method included meticulous preprocessing procedures such feature selection using SelectKBest, feature scaling using StandardScaler, and class balance using SMOTE. With an astounding accuracy of 99.70% and an AUC-ROC score of 0.9998, XGBoost surpassed Logistic Regression among the models used in all evaluation criteria, exhibiting exceptional predictive ability. A user-friendly Flask web application that lets users enter patient data and get real-time forecasts and a visual representation of the model's performance was also incorporated into the project. To improve usability and interpretability, additional features including dataset insights, algorithm accuracy visualization, and temporary user login were included. The study's findings demonstrate how optimal machine learning approaches can be used to create scalable and dependable healthcare prediction systems. This study can help with early diagnosis and better patient care in heart failure cases by acting as a fundamental paradigm for practical clinical decision support systems.

FUTURE ENHANCEMENT

In order to increase prediction accuracy and automatically extract intricate patterns from clinical data, this project may be improved in the future by including cutting-edge deep learning architectures like Artificial Neural Networks (ANN) or Convolutional Neural Networks (CNN). A real-time data collecting module linked to wearable health monitoring devices or hospital databases might be added to the current system to provide ongoing patient tracking and early risk alerts. The application would also be appropriate for real-world deployment if a secure database for patient records and user credentials were implemented. To support long-term healthcare analytics, the online interface can be extended to incorporate patient history management, trend analysis, and comprehensive visual dashboards. Additionally, using Explainable AI (XAI) methodologies would increase transparency and trust by assisting clinicians in understanding how predictions are made. Lastly, by including more medical datasets, automating report production, and implementing the model on cloud infrastructure for scalability and accessibility across healthcare facilities, the system might develop into a complete clinical decision-support platform.

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