

Predicting the Classification of Heart Failure Patients Using Optimized Machine Learning Algorithms

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Abstract

Heart failure prediction is a critical task in healthcare analytics, enabling early diagnosis and timely intervention to reduce mortality rates. However, traditional clinical approaches often lack scalability and struggle to capture complex nonlinear relationships in patient data. To address these limitations, a machine learning-driven framework is developed using the healthcare-dataset-stroke-data, comprising diverse clinical attributes associated with cardiovascular conditions. The data undergoes preprocessing steps including duplicate removal, missing value imputation, label encoding, normalization via StandardScaler, genetic algorithm-based feature selection, and class balancing using SMOTE. Multiple models are implemented, including Support Vector Machine, Random Forest, and Gradient Boosting with GridSearch, Bayesian Optimization, and Particle Swarm Optimization, along with ensemble methods such as Voting and Stacking classifiers. Model performance is evaluated using accuracy, precision, recall, and F1-score, supported by confusion matrix analysis. Results show that Stacking and Voting classifiers achieve the highest performance of 0.971 across all metrics, outperforming optimized individual models, while Gradient Boosting with PSO performs best among single models. Furthermore, interpretability is enhanced using LIME and SHAP techniques, and a Flask-based interface enables real-time prediction deployment. This integrated approach improves both prediction accuracy and model transparency in heart failure classification.

Keywords: Cardiovascular diseases, Predictive models, Prediction algorithms, Machine learning algorithms, Accuracy, Machine learning, Computational modeling, Mortality, Adaptation models, Particle swarm optimization.

1. Introduction

Cardiovascular diseases (CVDs) constitute a major global health burden, encompassing conditions such as coronary artery disease, stroke, and heart failure (HF). According to the World Health Organization (WHO), CVDs are the leading cause of mortality worldwide, claiming nearly 17.9 million lives annually, which accounts for approximately 32% of all global deaths [1]. Among these, HF is particularly alarming, affecting more than 64.3 million individuals worldwide and imposing a significant economic strain on healthcare systems [2]. HF is a chronic, progressive disorder in which the heart loses its ability to pump blood effectively, leading to symptoms such as fatigue, breathlessness, and fluid retention. This condition often arises as a consequence of underlying risk factors like hypertension, diabetes, obesity, and prior cardiovascular complications [3].

Despite advances in diagnostic imaging, pharmacological interventions, and surgical procedures, the prognosis of HF remains dismal. Studies reveal that nearly 50% of patients diagnosed with HF die within five years of diagnosis, highlighting its severity and persistent challenge in cardiovascular medicine [4]. Such high mortality and morbidity underscore the pressing need for accurate, timely, and individualized prediction systems that can assist clinicians in tailoring interventions and improving outcomes.

The growing availability of electronic health records (EHRs), biomedical sensors, and large-scale clinical datasets has opened pathways for the integration of machine learning (ML) into cardiovascular healthcare [5]. ML algorithms are capable of uncovering hidden patterns, relationships, and trends within complex datasets, thereby offering valuable tools for predicting patient outcomes, stratifying risks, and personalizing treatment strategies. Specifically, the prediction of HF progression and mortality using ML has garnered significant attention due to its potential to enhance clinical decision-making and optimize resource allocation [6].

However, one of the major limitations in deploying ML for HF prediction is ensuring model robustness and generalizability across diverse patient populations. Traditional models often suffer from reduced performance when applied to heterogeneous datasets, primarily due to suboptimal hyperparameter selection and class imbalance issues [7]. To address these challenges, researchers are increasingly focusing on optimization techniques, such as grid search, random search, and evolutionary algorithms, which can fine-tune hyperparameters and significantly improve predictive accuracy [8]. These optimization strategies, when combined with advanced ML algorithms, present a promising avenue to build reliable models that can assist in the early prediction and effective management of HF patients.

2. Related Work

The diagnosis and management of heart failure (HF) have been shaped considerably by clinical guidelines and technological advancements over the past decades. McDonagh et al. [9] in the 2021 European Society of Cardiology (ESC) guidelines emphasized updated recommendations for the diagnosis and treatment of both acute and chronic HF, building on evolving clinical practices and incorporating recent evidence from large-scale trials. These guidelines offered detailed strategies for patient risk stratification, pharmacological management, and device-based therapies, ensuring that clinicians could provide evidence-based care. Importantly, the guidelines recognized the potential of artificial intelligence (AI) and machine learning (ML) tools as emerging adjuncts to traditional methods, setting the stage for further integration of predictive analytics in cardiovascular medicine. Similarly, Ponikowski et al. [13] in the earlier 2016 ESC guidelines laid the foundation by providing standardized criteria for HF diagnosis and treatment, offering essential insights into disease classification, ejection fraction-based subtypes, and therapeutic approaches. Together, these guidelines have served as a benchmark for clinical practice while also highlighting the need for innovative approaches that extend beyond conventional diagnosis and therapy.

In parallel with clinical guidelines, several studies have focused on improving prognostic prediction and patient outcomes through advanced analytics. Angraal et al. [10] conducted a study applying machine learning techniques to predict mortality and hospitalization among patients with HF with preserved ejection fraction (HFpEF). Their work demonstrated that ML models could outperform traditional statistical approaches in identifying high-risk patients, particularly by analyzing large volumes of structured and unstructured clinical data. This study addressed the growing challenge of HFpEF, a condition with limited therapeutic options, and showed how predictive analytics could guide personalized care. Complementing this, Ahmad et al. [12] performed a survival analysis of HF patients using clinical datasets to evaluate prognostic factors influencing mortality. Their findings confirmed that age, comorbidities, and clinical parameters significantly affect survival outcomes, while also demonstrating the potential of statistical and computational models in patient monitoring. Both studies emphasized the need for predictive approaches that integrate multi-dimensional patient information to support early intervention strategies.

Global epidemiological perspectives have also been critical in framing the HF burden. Savarese and Lund [11] provided an in-depth review of the public health burden of HF, illustrating its prevalence, incidence, and socio-economic impact. They highlighted that HF is not only a clinical challenge but also a pressing global health issue, particularly in aging populations where healthcare resources are strained. Their work underscored the importance of prevention, timely diagnosis, and cost-effective treatment approaches, all of which can be enhanced by predictive modeling and personalized medicine. Similarly, Ahmad et al. [12] reinforced the global challenge by focusing on patient-level survival analysis, demonstrating the variation in disease progression across different demographic and clinical groups.

As traditional regression-based statistical methods began to show limitations in handling complex, high-dimensional healthcare data, researchers advocated for the adoption of machine learning. Goldstein, Navar, and Carter [14] argued for moving beyond conventional regression techniques in cardiovascular risk prediction by highlighting the ability of ML to capture non-linear relationships, interactions, and heterogeneity in patient data. They demonstrated how ML methods could address challenges such as overfitting, missing data, and model interpretability while also providing more flexible and robust predictions compared to standard approaches. Their work was instrumental in motivating a shift toward the adoption of ML-based predictive analytics in cardiovascular medicine, bridging the gap between clinical epidemiology and computational sciences.

Building on this transition, Awan et al. [15] examined the readiness of machine learning in HF management, providing a critical review of ML applications in diagnosis, prognosis, and therapy optimization. They argued that while ML shows significant promise in improving HF outcomes, its application in clinical practice was still in early stages, requiring rigorous validation, interpretability, and integration into clinical workflows. They also highlighted specific ML techniques, such as decision trees, support vector machines, and ensemble methods, which had demonstrated promising results in predictive tasks. Their study provided valuable insights into the opportunities and challenges in translating ML research into clinical adoption, stressing the importance of balancing algorithmic accuracy with transparency and usability for healthcare providers.

Further extending the application of ML, Panahiazar et al. [16] explored using electronic health records (EHRs) for HF therapy recommendation through multidimensional patient similarity analytics. Their work introduced a novel approach to patient-centered decision support by comparing new patients with historical cases in terms of multidimensional clinical features, enabling personalized therapy recommendations. Unlike traditional models that rely heavily on generalized treatment pathways, this approach leveraged the richness of EHR data to enhance treatment precision and outcomes. This study illustrated the potential of ML to bridge the gap between population-level guidelines and individual patient needs, marking a significant step toward precision medicine in HF care.

3. Materials And Methods

The proposed system develops an optimized machine learning framework for heart failure prediction using the Heart Failure Clinical Records dataset (Kaggle). Data preprocessing is applied to manage missing values, encode categorical attributes, and standardize features. To address class imbalance, Synthetic Minority Oversampling Technique (SMOTE) and Random Over Sampling (ROS) are employed. Feature selection is performed using the Chi-square (χ^2) test to extract significant predictors. Multiple classifiers—Random Forest, Support Vector Machine (SVM), AdaBoost, Gradient Boosting Machine (GBM), and Stochastic Gradient Descent (SGD)—are trained and optimized through Artificial Immune Whale–Particle Swarm Optimization (AIW-PSO) for efficient hyperparameter tuning. Furthermore, Explainable AI (LIME) is incorporated to interpret influential features, and the trained models are deployed via a Flask-based web application for real-time clinical decision support.

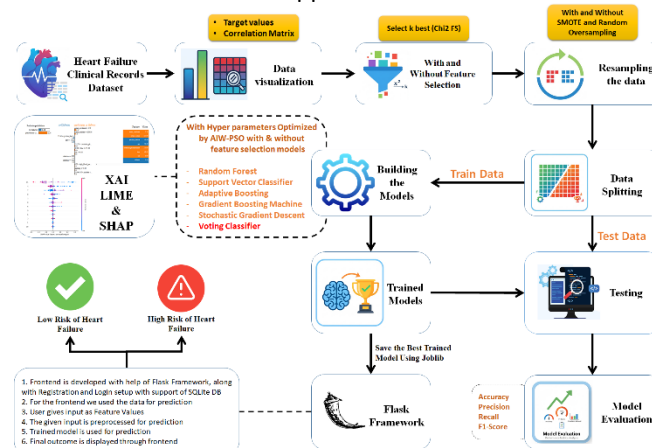


Fig. 1. System Architecture

The proposed system architecture illustrates a machine learning pipeline for heart failure clinical prediction. The process begins with dataset collection followed by preprocessing steps such as handling missing values, encoding categorical variables, feature standardization, and SMOTE balancing. χ^2 feature selection is applied, and data is split into training and testing sets with resampling methods. Various models are trained and evaluated using performance metrics like accuracy, precision, recall, and F1-score. Finally, the model is deployed via Flask, integrating explainable AI (XAI) to interpret predictions and return results to users.

A) Data Set Collection

The dataset used in this study is the healthcare-stroke dataset obtained from a publicly available machine learning repository. It comprises 5,110 patient records with 12 attributes, including demographic, clinical, and lifestyle-related features such as age, gender, hypertension, heart disease, glucose level, BMI, and smoking status. The dataset contains

a binary target variable indicating stroke occurrence. It includes both numerical and categorical data, with minor missing values in the BMI feature and class imbalance in the target variable. Its diverse clinical attributes and real-world characteristics make it well-suited for developing and evaluating robust predictive models in healthcare analytics.

	id	gender	age	hypertension	heart_disease	ever_married	work_type	residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1

Fig. 2. Dataset Collection

B) Pre-Processing:

Effective data preprocessing is essential for improving data quality, enhancing feature relevance, and ensuring reliable model performance. The following steps establish a structured pipeline for accurate and robust prediction.

Data Pre-processing and Cleaning: This step focuses on improving data quality by removing duplicate records and addressing missing values. Duplicate entries are eliminated to prevent bias and redundancy in model training, ensuring each observation contributes uniquely to learning. Missing values are handled through statistical imputation, which replaces incomplete entries with representative estimates. This process enhances dataset consistency and prevents information loss. Overall, it ensures a reliable and clean dataset, which is essential for building accurate and unbiased machine learning models.

Data Visualization: In this step, exploratory analysis is conducted to understand the underlying patterns and distributions within the dataset. Visual representations are used to analyze the target variable distribution, patient age trends, relationships between heart disease and outcomes, and inter-feature correlations. This helps identify class imbalance, detect potential outliers, and understand feature dependencies. Such insights guide informed decision-making in subsequent preprocessing and modeling stages, ultimately improving model interpretability and performance.

Feature Encoding: Feature encoding is applied to transform categorical variables into numerical representations suitable for machine learning algorithms. Since most models require numerical input, categorical attributes such as gender, work type, and smoking status are systematically converted into numeric form. This transformation preserves the inherent information while enabling efficient computation. Proper encoding ensures that the model can interpret categorical data effectively, contributing to improved learning and predictive accuracy.

Data Normalization: Data normalization is performed to scale numerical features into a standardized range, ensuring uniformity across all variables. This step is particularly important for algorithms sensitive to feature magnitude differences, as it prevents features with larger values from dominating the learning process. By standardizing the data distribution, the model achieves faster convergence and improved stability during training. Consequently, normalization enhances overall model performance and comparability across features.

Feature Selection: Feature selection is carried out using an optimization-based approach to identify the most relevant attributes contributing to prediction. By selecting an optimal subset of features, redundant and irrelevant information is eliminated, reducing model complexity and computational cost. This step enhances generalization capability and minimizes the risk of overfitting. It ensures that the model focuses only on significant patterns within the data, thereby improving accuracy and interpretability.

Data Balancing: To address class imbalance in the dataset, a resampling technique is applied to generate a more balanced distribution of classes. This step ensures that minority class instances are adequately represented during training, preventing bias toward the majority class. Balanced data improves the model's ability to correctly classify rare events, which is critical in healthcare applications. As a result, performance metrics such as recall and F1-score are significantly enhanced.

Train-Test Split: The dataset is divided into separate training and testing subsets to evaluate model performance objectively. The training set is used to learn patterns and relationships, while the testing set assesses how well the model generalizes to unseen data. This separation helps prevent overfitting and provides a realistic estimate of predictive capability. It is a fundamental step in ensuring the reliability and robustness of the developed machine learning system.

Hyperparameter Optimization: Hyperparameter optimization is performed to fine-tune model parameters for achieving optimal performance. Various optimization strategies are employed to systematically explore the parameter space and identify the best configurations. This process improves model accuracy, stability, and generalization by selecting parameters that best fit the data. Effective tuning ensures that each algorithm performs at its highest potential, contributing to the overall efficiency and robustness of the predictive framework.

C) Algorithms

Random Forest: Random Forest is an ensemble learning algorithm that improves prediction accuracy and robustness by constructing multiple decision trees and aggregating their outputs. It reduces overfitting and handles feature variability effectively, making it suitable for complex classification tasks with high reliability.

Support Vector Machine (SVM): Support Vector Machine is a supervised learning algorithm that performs classification by identifying an optimal decision boundary between classes. It is effective in handling high-dimensional data and ensures strong generalization by maximizing the margin between different class distributions.

Gradient Boosting: Gradient Boosting is an iterative ensemble technique that builds models sequentially, where each new model corrects the errors of previous ones. It enhances predictive performance by focusing on difficult instances, resulting in improved accuracy and reduced bias.

Voting Classifier: Voting Classifier is an ensemble approach that combines predictions from multiple models to produce a final decision. By leveraging the strengths of different algorithms, it improves overall accuracy, stability, and robustness through collective decision-making.

Stacking Classifier: Stacking Classifier is an advanced ensemble technique that integrates multiple base models and uses a meta-model to combine their predictions. This layered approach enhances generalization and predictive performance by learning optimal combinations of individual model outputs.

H) Integration of XAI and Flask Framework:

The system integrates Explainable AI (XAI) techniques to enhance transparency and interpretability of model predictions. Methods such as Local Interpretable Model-Agnostic Explanations and Shapley Additive Explanations are utilized to provide both local and global insights into feature contributions. These techniques help in understanding the influence of individual features on prediction outcomes, thereby improving trust and reliability in decision-making. The visualization of explanations enables users to interpret complex model behavior effectively.

The frontend is implemented using a lightweight web framework, facilitating seamless interaction between users and the predictive model. It incorporates user authentication supported by a structured database system to ensure secure access. The interface collects user input, which is preprocessed and forwarded to the trained model for prediction. The system then displays results in real time, ensuring an interactive and user-friendly environment for practical deployment.

Experimental Results

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (6)$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (7)$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN} \quad (8)$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$F1\ Score = 2 * \frac{Recall \times Precision}{Recall + Precision} * 100(9)$$

Table. 1. Performance Evaluation

ML Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.945	0.946	0.945	0.945
SVM	0.938	0.940	0.938	0.938
Gradient Boosting	0.956	0.957	0.956	0.956
Voting Classifier	0.971	0.971	0.971	0.971
Stacking Classifier	0.971	0.971	0.971	0.971

Table.1 presents the performance evaluation of five machine learning models, where ensemble methods, particularly Voting and Stacking classifiers, achieve the highest accuracy and overall metrics, outperforming individual models in classification effectiveness.

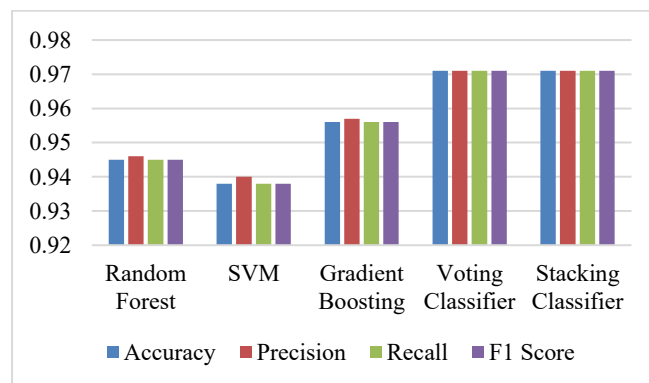


Fig. 3. Comparison Graph

Fig.3 illustrates the comparative performance of five machine learning models, highlighting that Voting and Stacking classifiers achieve superior results across all metrics, while Gradient Boosting outperforms other individual models in overall accuracy.

HEARTSYNC

Home | Graphs | Notebook | Logout

Yes | Government Job

Residence Type: Rural | Avg. Glucose Level: 120.46

BMI: 36.8 | Smoking Status: Smokes

Run Classification

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Fig.4 Enter the input Data

Fig.4 shows the user interface for inputting patient clinical details, including residence type, glucose level, BMI, and smoking status, enabling users to submit data and obtain real-time classification results.

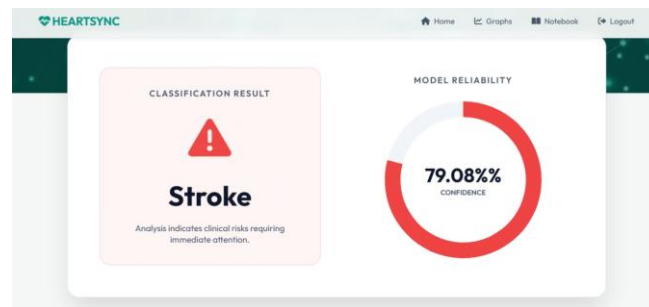


Fig.5 Predicted Result

Fig.5 displays the classification output indicating a stroke prediction with 79.08% confidence, highlighting potential clinical risk and emphasizing the need for timely medical evaluation and appropriate intervention.

HEARTSYNC

Home | Graphs | Notebook | Logout

Ever Married: No | Work Type: Private

Residence Type: Rural | Avg. Glucose Level: 85.37

BMI: 33 | Smoking Status: Never Smoked

Run Classification

Fig.6 Enter the input Data

Fig.6 presents the user interface for entering patient details such as marital status, work type, glucose level, BMI, and smoking status, enabling users to input data for prediction analysis.

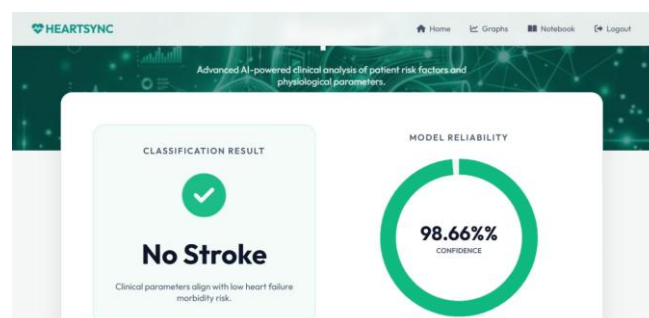


Fig.7 Predicted Result

Fig.7 illustrates the classification output indicating no stroke condition with a confidence of 98.66%, demonstrating low clinical risk and confirming the effectiveness of the predictive model in accurate diagnosis.

4. Conclusion

The system demonstrates an effective approach for heart failure classification by integrating optimized machine learning algorithms with ensemble learning techniques. Comprehensive preprocessing, including data cleaning, normalization, feature selection using Genetic Algorithms, and class balancing with SMOTE, significantly improved data quality and model robustness. The application of multiple optimization strategies—GridSearch, Bayesian Optimization, and Particle Swarm Optimization—enhanced the performance of individual classifiers such as Support Vector Machine, Random Forest, and Gradient Boosting. Among these, ensemble methods, particularly Voting and Stacking classifiers, achieved superior performance, attaining the highest accuracy, precision, recall, and F1-score of 0.971, thereby outperforming all optimized standalone models. In addition to predictive performance, the incorporation of explainable AI techniques, namely LIME and SHAP, provided meaningful insights into feature importance and model decision-making, addressing the critical requirement of transparency in healthcare applications. Furthermore, the deployment of the trained model through a Flask-based interface enables real-time prediction and user interaction, enhancing practical usability. Overall, the integration of optimization, ensemble learning, and interpretability techniques results in a reliable and scalable system for heart failure prediction. Future improvements may focus on incorporating larger and more diverse datasets to further enhance generalization and clinical applicability.

Future work can focus on incorporating larger, multi-institutional datasets to improve model generalization and robustness across diverse populations. Integration of deep learning techniques and hybrid models may further enhance predictive accuracy. Real-time data acquisition from wearable devices and electronic health records can enable continuous monitoring and early risk detection. Additionally, improving explainability through advanced XAI methods and expanding the system into a cloud-based or mobile healthcare platform can increase accessibility, scalability, and practical clinical adoption.

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