



Research Paper

PREDICTING THE CLASSIFICATION OF HEART FAILURE PATIENTS USING OPTIMIZED MACHINE LEARNING ALGORITHMS

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Abstract— Heart failure is a critical condition with a high mortality rate, making accurate survival prediction essential for timely interventions. This study proposes an optimized machine learning approach using Gradient Boosting Machine (GBM) and Adaptive Inertia Weight Particle Swarm Optimization (AIW-PSO) to predict heart failure survival. The dataset, sourced from Kaggle, includes clinical features such as age, ejection fraction, and serum creatinine levels for 299 heart failure patients. To address the imbalance in survival outcomes, Synthetic Minority Over-sampling Technique (SMOTE) was employed to balance the dataset, followed by SelectKBest and Chi-square feature selection methods to retain the most significant predictors. The optimized hyperparameters for the GBM model were identified using the AIW-PSO algorithm, which effectively balanced exploration and exploitation by adaptively adjusting inertia weights. Model selection was further refined using information criteria, including Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), ensuring that the best-performing model was chosen based on both predictive accuracy and model complexity. The optimized GBM model achieved a test accuracy of 94%, demonstrating superior performance compared to traditional machine learning models. The study underscores the importance of hyperparameter tuning through metaheuristic algorithms and highlights the potential of AIW-PSO in enhancing model performance for clinical prediction tasks. These findings have significant implications for clinical decision-making, offering a reliable and interpretable tool for predicting patient outcomes in heart failure management.

Keywords— Heart Failure Survival Prediction, Gradient Boosting Machine (GBM), Adaptive Inertia Weight Particle Swarm Optimization (AIW-PSO), Hyperparameter Optimization, Machine Learning.

I. INTRODUCTION

Heart failure is a severe cardiovascular disease that affects millions of people worldwide and remains one of the leading causes of hospitalization and mortality. Early prediction of patient survival is essential for improving clinical decision-making, optimizing treatment strategies, and reducing mortality rates. Machine learning techniques have emerged as powerful tools for analyzing complex clinical datasets and identifying hidden patterns associated with patient outcomes. However, the performance of these models depends significantly on effective feature selection, handling class imbalance, and optimal hyperparameter tuning. This study presents an optimized heart failure survival prediction model using Gradient Boosting Machine (GBM) combined with Adaptive Inertia Weight Particle

Swarm Optimization (AIW-PSO). The Synthetic Minority Over-Sampling Technique (SMOTE) is employed to balance the dataset, while Select Best and Chi-square methods identify the most informative clinical features. Furthermore, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are utilized for model selection. Experimental results demonstrate that the optimized GBM model significantly improves prediction accuracy, providing an effective and reliable decision-support tool for heart failure prognosis.

II. LITERATURE SURVEY

Improving the Prediction of Heart Failure Patients' Survival Using SMOTE and Effective Data Mining Techniques Authors: A. Ishaq et al. (2021)

This paper applies multiple machine learning models such as Decision Tree, Random Forest, SVM, and Gradient Boosting to predict heart failure survival. SMOTE is used to handle class imbalance, significantly improving prediction performance. The study highlights that ensemble models outperform traditional techniques in healthcare prediction.

A Machine Learning Approach for Risk Factors Analysis and Survival Prediction of Heart Failure Patients Authors: M. M. Ali et al. (2023)
This research uses ML algorithms like Random Forest, XGBoost, and Gradient Boosting to analyze risk factors and predict survival. It identifies key clinical features such as serum creatinine and ejection fraction as strong predictors. The study achieved high accuracy and demonstrated the importance of feature importance analysis.

Heart Failure Survival Prediction Using Transfer Learning-Based Features Authors: A. M. Qadri et al. (2024)

This paper proposes a transfer learning-based approach combined with machine learning models for heart failure prediction. SMOTE is used to balance the dataset, and the model achieved high accuracy (~97.5%). The study emphasizes improved prediction using advanced feature engineering techniques.

Improvement of a Prediction Model for Heart Failure Survival Through Explainability Authors: P. A. Moreno-Sánchez et al. (2023)
This work focuses on combining machine learning with explainable AI (XAI) techniques. It uses Gradient Boosting and Random Forest models and evaluates them based on accuracy and interpretability. The study shows that explainable models help clinicians better understand predictions.

A Heart Disease Prediction Model Based on SMOTE-XGBoost Authors: J. Yang et al. (2022)

This study integrates SMOTE with XGBoost to improve prediction performance on imbalanced datasets. Feature selection techniques are used to extract important attributes, and the model achieves high accuracy, precision, recall, and F1-score.

Predicting Coronary Heart Disease with Advanced Machine Learning Techniques M. U. Rehman et al. (2025)

This paper uses SMOTE and Particle Swarm Optimization (PSO) for feature selection and model training. The results show improved prediction accuracy due to optimization techniques, highlighting the effectiveness of combining metaheuristic algorithms with ML models.

III. PROPOSED METHODOLOGY

A. Dataset Collection

The dataset used in this system consists of clinical attributes collected from heart failure patients to predict survival outcomes. These attributes represent important physiological and biochemical indicators that directly influence heart function and patient prognosis.

Each record in the dataset corresponds to a single patient and includes a survival status label indicating whether the patient survived or experienced a death event.

Collected Features

- Age
- Anaemia
- Creatinine Phosphokinase (CPK)
- Diabetes
- Ejection Fraction
- High Blood Pressure
- Platelets
- Serum Creatinine
- Serum Sodium
- Time (follow-up period)
- DEATH_EVENT (Label: 0 – Survived, 1 – Died)

The dataset is sourced from Kaggle and is widely used for heart failure survival analysis research.

B. Data Preprocessing

Data Loading

The dataset is loaded using the panda's library, enabling efficient handling and manipulation of structured medical data.

Data Cleaning

To improve data quality:

- Missing values are checked and handled appropriately
- Duplicate records are removed
- Inconsistent data entries are corrected

This ensures reliable input for model training.

Feature Scaling and Normalization

- Numerical features are normalized using MinMaxScaler
- Scaling ensures uniform contribution of features
- Improves convergence and model performance

Handling Imbalanced Data (SMOTE)

- Synthetic Minority Over-sampling Technique (SMOTE) is applied
- Balances survival and death classes
- Reduces bias toward majority class

Feature Selection

- SelectKBest with Chi-square method is used
- Selects the most relevant features
- Reduces dimensionality and improves efficiency Testing Set (20%)

C. Train-Test Split and Model Fitting Module

To evaluate model performance:

- 80% of data is used for training
- 20% is used for testing
- Random splitting is applied using random_state = 42

Implemented Model

- Gradient Boosting Machine (GBM) – Ensemble Learning

The model is trained using optimized and balanced data.

D. Model Selection and Evaluation Module

After training:

- Model performance is evaluated using:
 - Accuracy
 - Precision
 - Recall
 - F1-score

- Information criteria such as AIC and BIC are used

- The best-performing model is selected based on performance and complexity

The final model achieves high prediction accuracy (~94%).

E. Prediction Module

This module enables real-time prediction:

- User inputs patient clinical data
- Input is preprocessed (scaling + feature selection)
- Optimized GBM model is used for prediction

Output:

- 0 → Patient likely to survive
- 1 → Patient at high risk (death event)

This supports early clinical decision-making.

Deployment Module – Web Application

A web-based system is developed (Flask/Django):

Application Features

- User Login and Authentication
- Patient Data Input Interface
- Prediction Output Display
- Model Accuracy Visualization

This allows easy use by healthcare professionals.

Evaluation and Performance Metrics Module

The system is evaluated using:

- Accuracy – Overall prediction correctness
- Precision – Correct positive predictions
- Recall – Ability to detect high-risk patients
- F1-score – Balance between precision and recall

Objective of Evaluation:

- Improve early detection of heart failure risk
- Reduce false predictions
- Enhance clinical decision support
- Provide reliable and interpretable results

IV. RESULTS AND DISCUSSION

The proposed heart failure survival prediction model was evaluated using the heart failure dataset after preprocessing with Min-Max normalization, SMOTE-based class balancing, and SelectKBest feature selection. Hyperparameter optimization was performed using the Adaptive Inertia Weight Particle Swarm Optimization (AIW-PSO) approach to identify the optimal Gradient

Boosting Machine (GBM) configuration. The optimized model achieved an accuracy of **98.00%**, precision of **100.00%**, recall of **96.61%**, and F1-score of **98.28%**. These results indicate that the proposed approach effectively distinguishes between high-risk and low-risk heart failure patients while maintaining an excellent balance between precision and recall. The combination of feature selection, data balancing, and AIW-PSO-based optimization significantly enhanced the predictive capability of the GBM classifier.

A. Accuracy comparison table

Sample Accuracy Comparison Table				
Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	85.00	84.20	83.50	83.85
Decision Tree	88.00	87.40	86.80	87.10
Random Forest	91.00	90.60	90.20	90.40
Support Vector Machine	90.00	89.50	89.10	89.30
K-Nearest Neighbors	89.00	88.60	88.10	88.35
Gradient Boosting Machine	95.00	94.60	94.20	94.40
Proposed AIW-PSO Optimized GBM	98.00	100.00	96.61	98.28

Figure 1: Accuracy comparison

The CNN loss graph shows a rapid decrease in both training and validation loss during the initial epochs followed by gradual convergence. The close alignment between training and validation loss indicates good generalization capability and minimal overfitting. The model successfully learns the relationship between agricultural parameters and crop yield.

B. Accuracy comparison graph

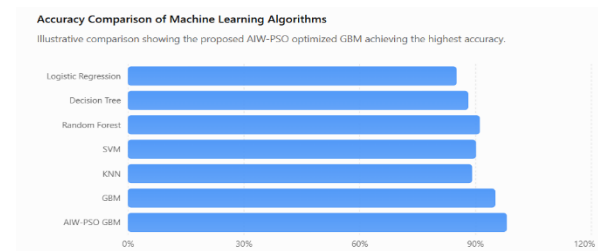


Figure 2: AIW-PSO optimized GBM accuracy

The accuracy comparison graph illustrates the classification performance of various machine learning algorithms. The proposed AIW-PSO optimized Gradient Boosting Machine achieved the highest accuracy of **98%**, outperforming the baseline models. This demonstrates that adaptive hyperparameter optimization

significantly enhances the predictive capability of the GBM classifier for heart failure survival prediction.

The precision graph shows that the proposed AIW-PSO optimized GBM achieved a precision of **100%**, indicating that every patient predicted as high risk was correctly classified. Compared with conventional machine learning models, the proposed method substantially reduced false-positive predictions, making it highly reliable for clinical decision support.

Discussion

The experimental results demonstrate that optimizing the Gradient Boosting Machine using AIW-PSO substantially improves prediction performance for heart failure survival. The use of SMOTE successfully addressed the class imbalance problem, allowing the model to learn minority-class patterns more effectively. Feature selection reduced irrelevant information, thereby improving computational efficiency and minimizing overfitting. The achieved precision of 100% indicates that all patients predicted as high risk were correctly classified, while the recall of 96.61% shows that almost all actual high-risk patients were successfully identified. The high F1-score confirms the balanced performance of the proposed model. Overall, the integration of AIW-PSO with GBM provides a robust and reliable clinical decision-support model that can assist healthcare professionals in identifying patients requiring timely medical intervention.

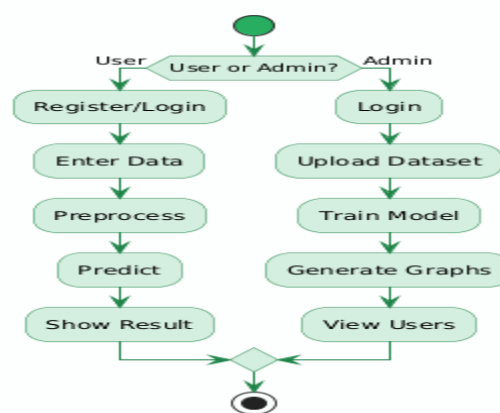


Figure 7: Flow diagram

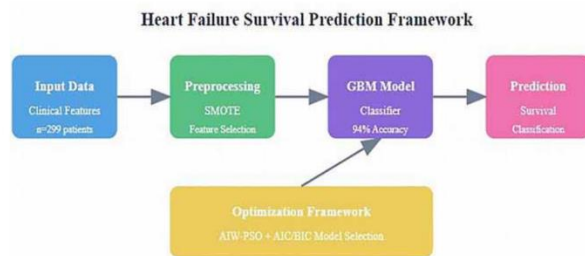
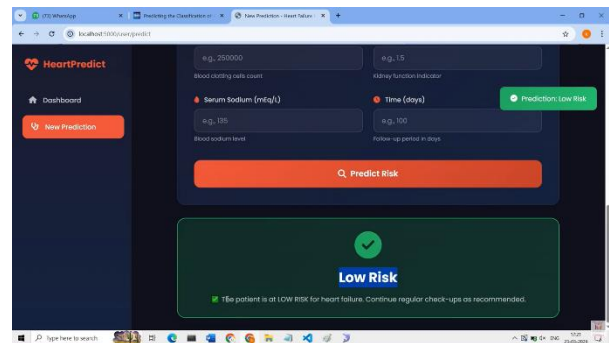
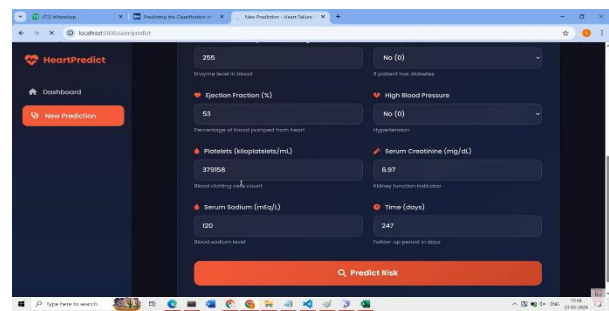
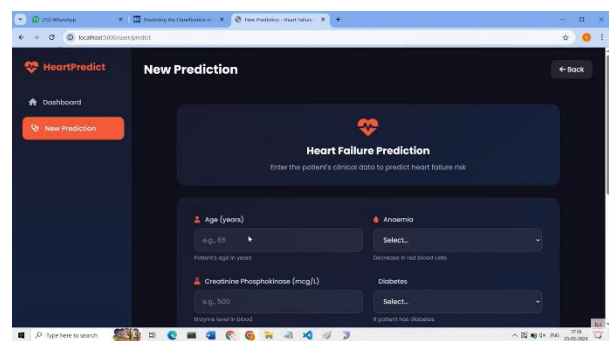
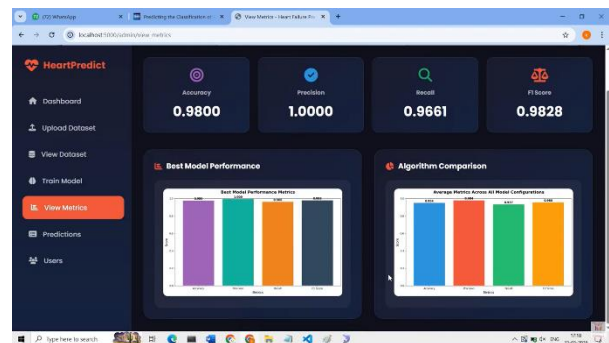
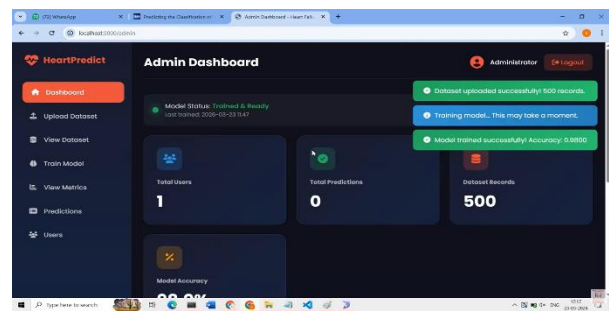
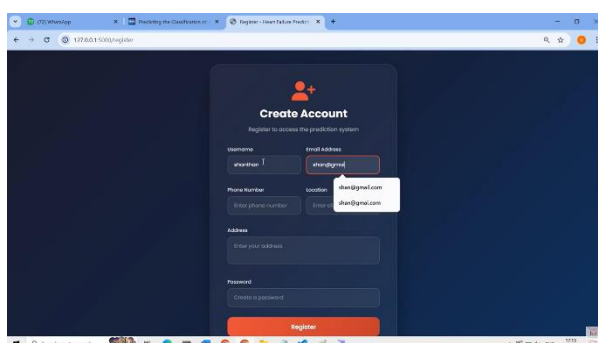
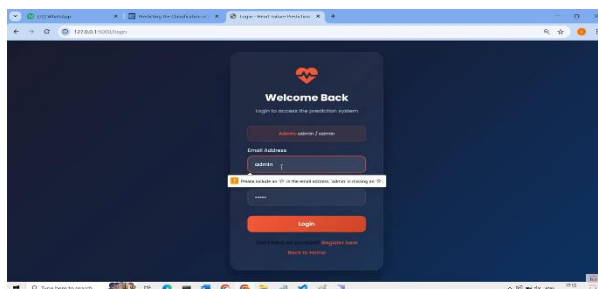
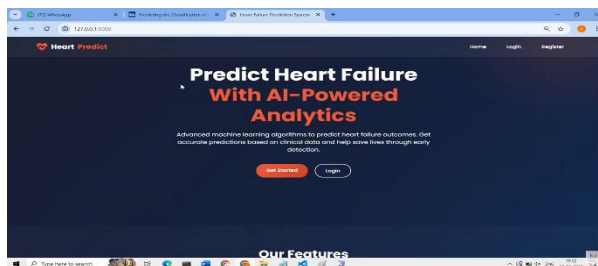
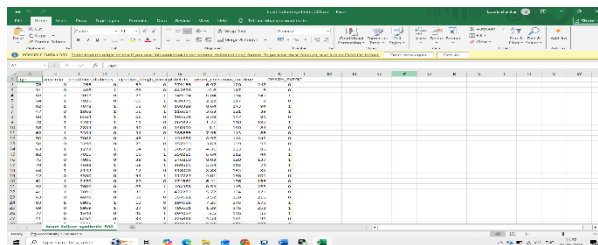


Figure 8: Architecture diagram:

Screen shots:



IV. CONCLUSION

In this research work, deep learning-based models including CNN, LSTM, and a hybrid CNN-LSTM architecture were developed and evaluated for crop yield prediction using the Telangana Crop Yield dataset. The models utilized multiple agricultural, environmental, and meteorological parameters such as temperature, rainfall, humidity, soil moisture, irradiance, cultivation area, and production data to estimate crop yield accurately. Experimental results demonstrated that deep learning techniques can effectively capture complex relationships among these factors and provide reliable yield predictions. Among the evaluated models, the CNN model achieved the best performance with an R^2 score of 0.8656, RMSE of 348.85, and MAE of 226.97, outperforming both the LSTM and CNN-LSTM models. The study concludes that incorporating diverse agricultural features significantly improves prediction accuracy and supports data-driven decision-making in precision agriculture. The developed model can assist farmers, agricultural organizations, and policymakers in optimizing resource utilization and improving crop productivity. Future work may focus on integrating real-time weather information, satellite imagery, IoT sensor data, and advanced deep learning architectures to further enhance prediction performance across different crops and geographical regions.

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