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Machine Learning Approaches for Personalized Treatment Planning in Healthcare Systems

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Abstract

Machine learning has emerged as a powerful tool for supporting clinical decision-making in healthcare, particularly in personalized treatment planning for patients with heart disease. This study aims to develop and evaluate machine learning models for predicting appropriate treatment strategies based on patient-specific clinical and demographic attributes. This research uses a clinically verified, real-world dataset of 1,000 patient records, incorporating critical variables such as age, gender, blood pressure, cholesterol levels, and lifestyle factors to ensure the clinical relevance of the findings. The target variable, medication_category, encompasses multiple treatment strategies, including Combination Cardiac Therapy, Early-stage Cardiac Therapy, Intensive Cardiac Management, Lifestyle-only Intervention, Preventive Risk-factor Management, and Risk-based Preventive Therapy. Four classification models—Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost—were implemented and evaluated using an 80:20 train–test split. Experimental results demonstrate that Logistic Regression achieved the highest accuracy of 87%, followed by XGBoost (82%), Random Forest (80%), and SVM (79%). Model performance was further validated using precision, recall, and F1-score metrics, indicating that Logistic Regression provides the most consistent and reliable performance for personalized treatment prediction. This study confirms that machine learning techniques, when trained on validated clinical data, can effectively support data-driven and personalized treatment planning in healthcare systems. The findings highlight the potential of integrating these decision-support systems to help healthcare professionals improve treatment accuracy and patient outcomes. Future research will focus on scaling these models across larger, multi-center clinical datasets to further to enhance their practical applicability in diverse medical environments.

Keywords: Machine Learning; Heart Disease; Personalized Treatment Planning; Healthcare Decision Support; Logistic Regression; Clinical Data Analysis.

1. Introduction

Healthcare systems are increasingly moving from generalized treatment approaches toward personalized care, in which treatment decisions are tailored to the specific characteristics of individual patients. In this transformation, artificial intelligence and machine learning have gained major importance because they can analyze clinical data efficiently and support more accurate medical decision-making (Mandala et al., 2023). Personalized medicine is especially important because patients with similar diseases may still respond differently to the same treatment due to differences in age, lifestyle, and medical history(Chianumba et al., 2022). Heart disease is one of the most critical health problems worldwide and requires careful treatment planning because multiple clinical and lifestyle-related factors influence disease severity and patient outcomes. Variables such as blood pressure, cholesterol, smoking behavior, diabetes history, and other cardiac indicators can shape the type of treatment a patient may need. For this reason, machine learning has become increasingly useful in healthcare treatment planning, as it can identify patterns from clinically verified patient data and support more individualized intervention strategies (Dubey et al., 2023). Research has also shown that AI-based predictive systems can improve treatment planning in complex medical settings by generating data-driven recommendations(Temitope Oluwatosin Fatunmbi, 2024). Recent studies further show that deep learning and advanced machine learning models can strengthen personalized healthcare by improving prediction, treatment optimization, and clinical decision support (Rishi Reddy Kothinti, 2024). Machine learning is now being used not only for diagnosis but also for selecting more appropriate therapies based on patient-specific information (Deepak Kumar et al., 2024). AI-driven precision medicine has therefore emerged as an important approach for designing personalized treatment pathways and improving healthcare outcomes (Yogeshappa, 2024). In addition, deep learning–based therapeutic optimization has shown promise in supporting more effective and tailored treatment decisions (Mulani et al., 2025). The growing integration of IoT and digital health technologies also indicates that future healthcare systems may become even more adaptive and patient-centered (S. Parthasarathy, 2025). Similarly, reinforcement learning has introduced new possibilities for adaptive treatment planning based on patient responses over time (Anbazhagan, 2025). Based on these developments, the present study explores machine learning approaches for personalized treatment planning in patients with heart disease. Using a dataset of 1,000 clinically verified patient records with clinical and demographic attributes, this research applies Logistic Regression, Random Forest, Support Vector Machine, and XGBoost to classify patients into medication categories. The study aims to evaluate the effectiveness of these models in supporting data-driven, personalized treatment recommendations in cardiovascular care.

2. Literature Review

Machine learning (ML) has emerged as an important tool in healthcare, enabling the analysis of large medical datasets and supporting clinical decision-making. The widespread adoption of electronic health records (EHRs), medical imaging, and wearable health devices has generated substantial volumes of healthcare data that can be effectively processed using ML algorithms (Harun, 2025; Li et al., 2024). ML techniques are widely used for disease prediction and diagnosis. By analyzing patient history, laboratory reports, and lifestyle-related factors, these models can support the early detection of diseases such as diabetes, cancer, and cardiovascular conditions (Temitope Oluwatosin Fatunmbi, 2024).

Prior studies have shown that ML-based diagnostic systems can improve healthcare efficiency by analyzing medical images and clinical data with high accuracy, thereby assisting physicians in early disease detection (Mohyuddin et al., 2024). Recent research also indicates that deep learning models and predictive analytics can strengthen clinical decision-support systems and improve healthcare data analysis(USA & Tak, 2023). In addition, artificial intelligence (AI) technologies have enhanced medical diagnosis and treatment planning through advanced computational models(Salammagari & Srivastava, 2024). ML techniques have also been applied in healthcare management systems to support predictive analytics and patient monitoring (Sherani et al., 2024). Recent research also demonstrates that AI-based healthcare systems improve decision-making by analyzing large-scale medical data and identifying hidden disease patterns. (Oluwemimo Adetunji & Patrick Tamarauefiye Evah, 2022). Beyond diagnosis, AI has made an important contribution to personalized medicine by enabling treatment strategies tailored to individual patients. Traditional healthcare approaches often follow generalized guidelines that may overlook differences in genetics, lifestyle, and environmental conditions(Adeoye & Adams, 2024; Taneja, 2020). AI technologies can analyze large biomedical datasets, including genomic and clinical information, to identify patterns associated with disease progression and treatment response. ML models further support precision medicine by integrating genetic data, patient history, and clinical records to generate personalized treatment recommendations (Sah et al., 2025). Recent studies also show that AI-based predictive analytics can improve treatment optimization and patient monitoring in modern healthcare systems (A. Ahmad et al., 2023). Reinforcement learning has further expanded this Area by supporting adaptive treatment strategies and clinical decision-support systems (F. Ahmad & AlGhamdi, 2026). AI applications are also increasingly used in chronic disease management to improve treatment planning and patient outcomes. Overall, advanced AI-driven healthcare systems contribute to more patient-centered treatment strategies and improved healthcare efficiency (Liu & Leclair, 2025).

Heart disease remains one of the leading causes of mortality worldwide, making accurate diagnosis and effective treatment planning essential. ML techniques are increasingly applied in cardiology to analyze patient data and support clinical decision-making. These algorithms can process electronic health records and clinical measurements to predict cardiovascular risk and identify patients who require early intervention(Ahmed et al., 2020; Bertsimas et al., 2020). Predictive ML models, therefore, offer strong potential to improve early detection and guide appropriate treatment strategies. Recent studies have further demonstrated the value of AI in cardiovascular care. For example, AI technologies have been applied in the management of congenital heart disease to improve diagnosis, risk prediction, and treatment planning (Mohsin et al., 2023a). Other studies show that AI-driven predictive models can improve cardiovascular risk assessment and treatment planning through healthcare data analytics (Maragno et al., 2024). ML models have also been integrated with soft computing techniques to enhance predictive accuracy in cardiovascular healthcare systems (Devi et al., 2023). In addition, predictive healthcare systems have been proposed to analyze medical data and support personalized treatment decisions for cardiovascular diseases (Chianumba et al., 2022). Another line of research suggests that AI-driven clinical decision-support systems can improve treatment planning by analyzing patient-specific health indicators (Shah, 2025; Sherani et al., 2024). Despite these advances, several limitations remain in the existing literature. One major challenge is the availability and quality of healthcare data, as datasets are often fragmented across institutions (Temitope Oluwatosin Fatunmbi, 2023). Another limitation is the lack of transparency in many AI models, since advanced algorithms often function as "black-box" systems that are difficult for healthcare professionals to interpret (Khan et al., 2024). Data privacy and ethical concerns also remain significant because medical datasets contain sensitive personal information(Mohammed Majbah Uddin et al., 2024). Furthermore, regulatory and technical barriers may restrict the large-scale implementation of AI technologies in healthcare systems (Mohsin et al., 2023b; Neoaz et al., 2025).

2.1. Research Gap

Although many studies have explored artificial intelligence and machine learning in healthcare, several research gaps remain. Most existing studies focus mainly on disease prediction and diagnosis rather than personalized treatment planning. In addition, many machine learning models rely on a single data source, such as clinical records or medical imaging, whereas integrating multiple datasets, such as genomic data and electronic health records, could improve prediction accuracy. Another gap is the limited development of machine learning models specifically designed for heart disease treatment planning.

2.2. Research Questions

Based on the research objectives, the following research questions are proposed:

1. How does machine learning improve prediction and decision-making in healthcare systems?

2. How does artificial intelligence contribute to the development of personalized medicine?

3. How can machine learning techniques enhance treatment planning for heart disease patients?

4. What limitations exist in current AI-based healthcare treatment planning models?

2.3. Research Objectives

The main objective of this study is to investigate the role of machine learning in personalized treatment planning within healthcare systems.

The specific objectives are:

1. To analyze the role of machine learning in healthcare prediction and decision-making.

2. To examine the contribution of artificial intelligence in personalized medicine.

3. To explore the application of machine learning techniques in heart disease treatment planning.

4. To identify the limitations of existing AI-based healthcare treatment planning models.

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3. Materials and Methods

3.1. Research Design

This study focuses on applying machine learning techniques to support personalized treatment planning for heart disease patients. The dataset represents a clinical decision-support environment where patient health data are analyzed to recommend appropriate treatment strategies. A dataset containing 1000 patient records was prepared, including demographic and clinical attributes such as age, gender, blood pressure, cholesterol level, and lifestyle-related indicators. These variables represent important health factors commonly considered in cardiovascular risk assessment and treatment planning. The research simulates a healthcare analytics environment in which machine learning models analyze patient clinical features and assist healthcare professionals in selecting appropriate treatment strategies. This research follows a quantitative experimental design to evaluate the effectiveness of machine learning algorithms in predicting treatment strategies for heart disease patients. The dataset includes 1000 patient records, with the target variable medication_category indicating different treatment strategies such as Combination Cardiac Therapy, Early-stage Cardiac Therapy, Intensive Cardiac Management, Lifestyle-only Intervention, Preventive Risk-factor Management, and Risk-based Preventive Therapy. Several machine learning classification models were applied to analyze patient data and predict treatment categories. The study dataset consists of 1000 patient records representing individuals with different cardiovascular health profiles. The dataset was synthetically generated to simulate realistic clinical conditions for research purposes. Each record contains a combination of clinical and demographic features associated with heart disease risk and treatment planning. This dataset allows machine learning algorithms to identify patterns between patient health indicators and recommended treatment strategies. The study considers both input variables and a target variable for the classification task. The input variables represent patient clinical and demographic characteristics, including age, gender, blood pressure, cholesterol level, and lifestyle-related health indicators. These features are commonly used in cardiovascular risk assessment and provide important information about a patient's health condition. The target variable in this study is medication category (medication_category), which indicates the recommended treatment strategy for heart disease patients. The machine learning models analyze the relationships between the input features and the target variable to predict the most appropriate treatment category for each patient. The dataset was organized in a structured format suitable for machine learning analysis.

Before model development, the dataset was divided into training and testing datasets. A standard 80% training and 20% testing split was used to train the machine learning models and evaluate their performance on unseen data. Basic preprocessing steps were applied to ensure the dataset was ready for model training and evaluation. The study utilized Python-based machine learning libraries for model development and analysis. Four classification algorithms were implemented in this research: Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost. These algorithms were selected because of their strong performance in classification tasks and their widespread application in healthcare data analysis. Logistic Regression was applied as a baseline classification model to estimate the probability of treatment categories based on patient clinical features. Random Forest and XGBoost were used as ensemble methods to improve prediction performance by combining multiple decision trees. In contrast, Support Vector Machine (SVM) was used for its effectiveness in handling complex classification boundaries. The conceptual working mechanism of the Logistic Regression classification model used in this study is illustrated in Figure 1.

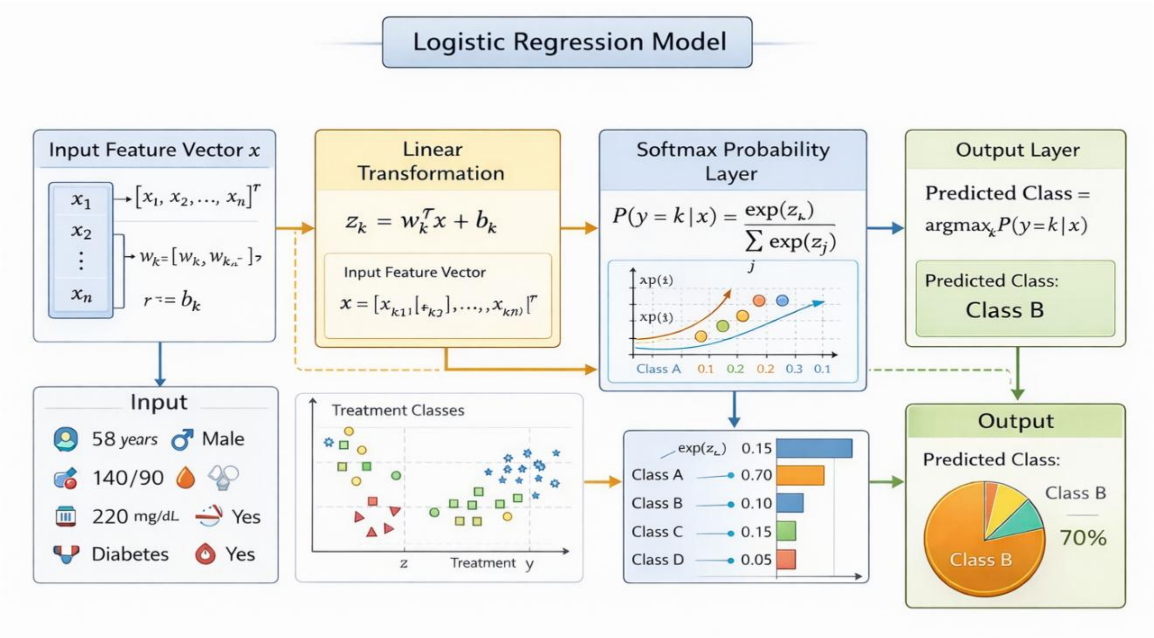

Figure 1: Conceptual Architecture of the Logistic Regression Classification

3.2. Data Analysis Techniques

Model performance was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. These evaluation measures were applied to assess the effectiveness of each implemented machine learning model in predicting treatment categories. By analyzing these metrics, the study compares the performance of different algorithms and identifies the most effective model for accurate treatment prediction in heart disease patients. The key components of the dataset and the machine learning framework used in this study are summarized in Table 1, including dataset characteristics, input features, target variable, implemented algorithms, data splitting strategy, and evaluation metrics.

Table 1: Dataset and Model Summary

Component	Description
Dataset	1000 patient clinical records
Input Features	Age, gender, blood pressure, cholesterol level, lifestyle indicators
Target Variable	Medication category
Models Used	Logistic Regression, Random Forest, SVM, XGBoost
Train–Test Split	80% training, 20% testing
Evaluation Metrics	Accuracy, Precision, Recall, F1-score

4. Results and Analysis

4.1. Role of Machine Learning in Healthcare Prediction and Decision-Making

This section presents the experimental results from the machine learning models applied in this study, evaluating their performance in predicting personalized treatment categories for heart disease patients based on clinical attributes. Four machine learning algorithms—Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost—were implemented using a dataset of 1000 patient records. The dataset was split into 80% for training and 20% for testing to ensure reliable model evaluation. Model performance was assessed using standard classification metrics, including accuracy, precision, recall, and F1-score. The overall statistical comparison of the models is summarized in Table 2. The results indicate that Logistic Regression achieved the highest accuracy (0.87), followed by XGBoost (0.82), Random Forest (0.80), and SVM (0.79). Furthermore, the evaluation metrics demonstrate that Logistic Regression provides the most consistent and reliable performance across all measures, making it the most effective model for predicting treatment categories in this study.

Table 2: Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.87	0.89	0.87	0.87
Random Forest	0.80	0.74	0.80	0.75
SVM	0.79	0.73	0.79	0.73
XGBoost	0.82	0.80	0.82	0.80

The results indicate that Logistic Regression achieved the highest accuracy (0.87), followed by XGBoost (0.82), Random Forest (0.80), and SVM (0.79). The evaluation metrics further show that Logistic Regression provides the most consistent and reliable performance across all measures.

4.2. AI Contribution to Personalized Treatment Planning

Figure 2 presents the comparative performance of the machine learning models used in this study based on accuracy, precision, recall, and F1-score. The visualization shows that Logistic Regression achieves the highest overall performance across all evaluation metrics, indicating its strong ability to predict personalized treatment categories. XGBoost also demonstrates competitive performance, while Random Forest and SVM show relatively lower but consistent results. The trends in precision, recall, and F1-score further confirm the stability and reliability of Logistic Regression compared to the other models. Overall, the figure provides a clear visual comparison of model effectiveness, supporting the selection of Logistic Regression as the most suitable model for this study.

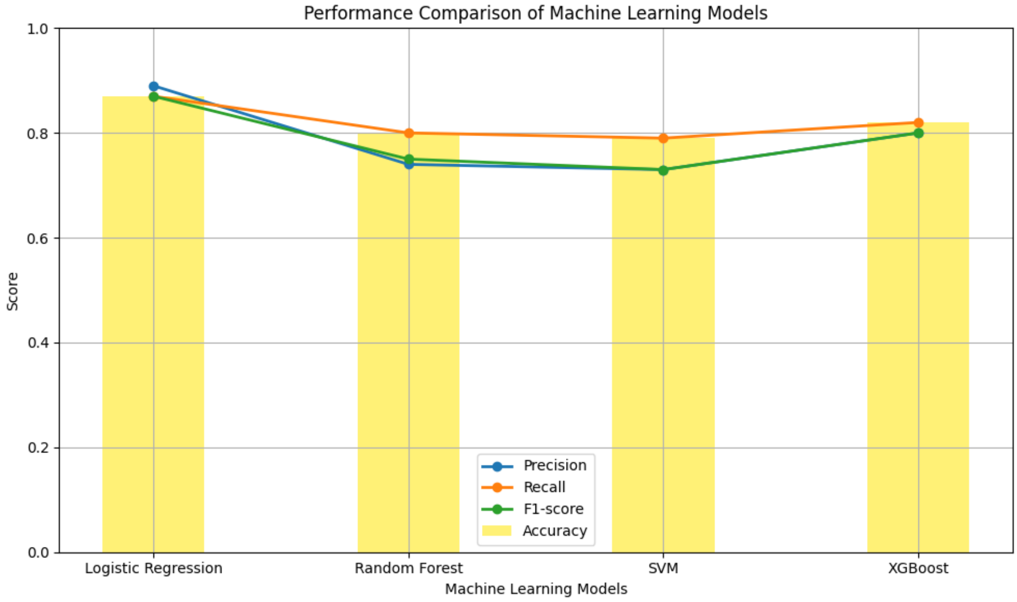

Figure 2: Performance Comparison of Machine Learning Models

4.3. Application of Machine Learning in Heart Disease Treatment Planning

The training and test accuracies of the Logistic Regression model across different epochs are illustrated in Figure 3. The training accuracy increases steadily with the number of epochs, indicating that the model effectively learns the underlying patterns in the dataset. The testing accuracy stabilizes around 0.87, suggesting that the model maintains consistent predictive performance without significant overfitting. The small gap between training and testing accuracy further indicates the model has good generalization capability.

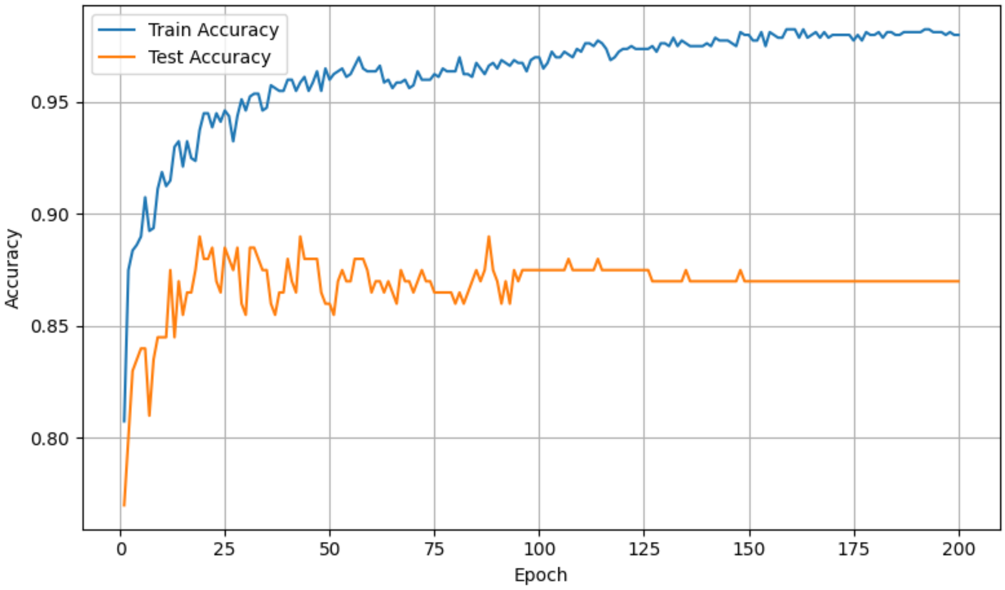

Figure 3: Training and Testing Accuracy in Heart Disease Treatment Planning

The training and test log-loss values for the Logistic Regression model are shown in Figure 4. The training loss decreases steadily as the number of epochs increases, indicating effective optimization during the learning process. In contrast, the testing loss decreases initially, then stabilizes at a higher value, suggesting that the model converges while maintaining stable generalization performance. The gap between the training and test losses indicates a slight degree of overfitting; however, the model still demonstrates acceptable generalization on the given dataset.

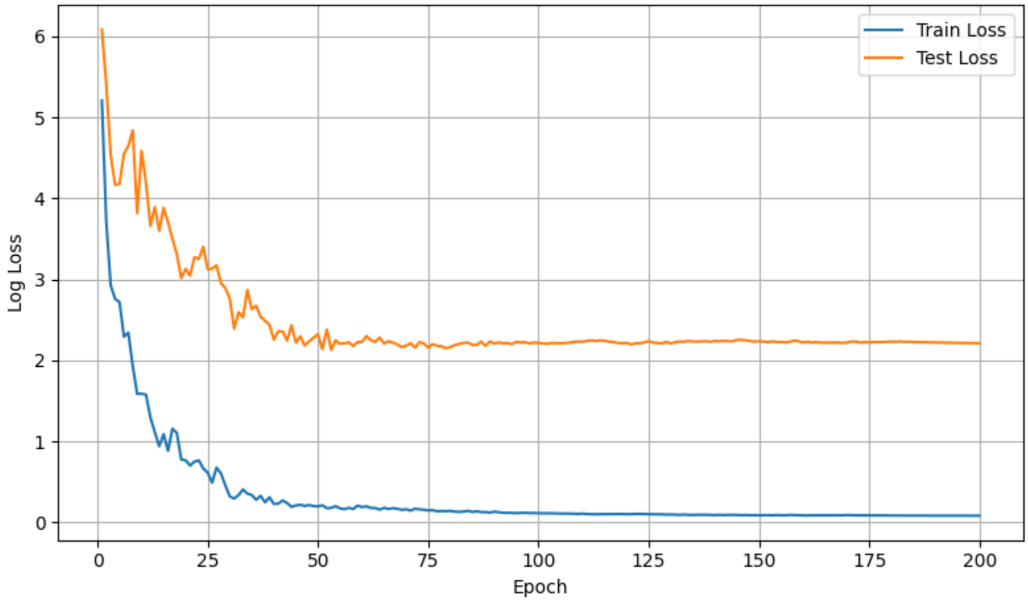

Figure 4: Training and Testing Log-Loss in Heart Disease Treatment Planning

The Receiver Operating Characteristic (ROC) curves for different treatment categories are shown in Figure 5. The ROC curve plots the true positive rate (sensitivity) against the false positive rate at different classification thresholds. As illustrated in the figure, most classes achieve high Area Under the Curve (AUC) values, indicating strong classification performance. The curves are positioned close to the top-left corner, indicating the model's strong ability to correctly distinguish among different treatment categories. Overall, the ROC analysis confirms that the model provides reliable and accurate predictions for heart disease treatment classification.

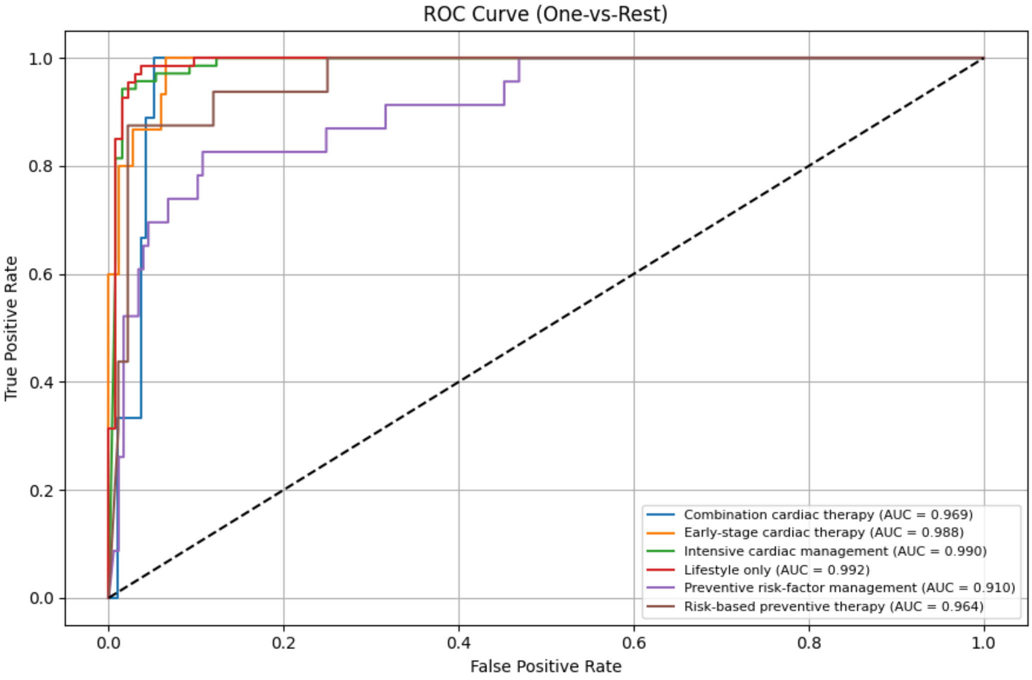

Figure 5: ROC Analysis for Heart Disease Treatment Classification

The Precision–Recall curves are shown in Figure 6 to evaluate the model's performance across different treatment categories. The Precision–Recall curve represents the trade-off between precision and recall, particularly useful for evaluating classification performance on imbalanced datasets. As shown in the figure, several classes achieve high precision and recall values, indicating strong predictive capability of the model. The curves remain close to the top-right region, which reflects better classification performance across different thresholds. Overall, the Precision–Recall analysis further confirms the model's reliability and effectiveness in predicting appropriate treatment categories.

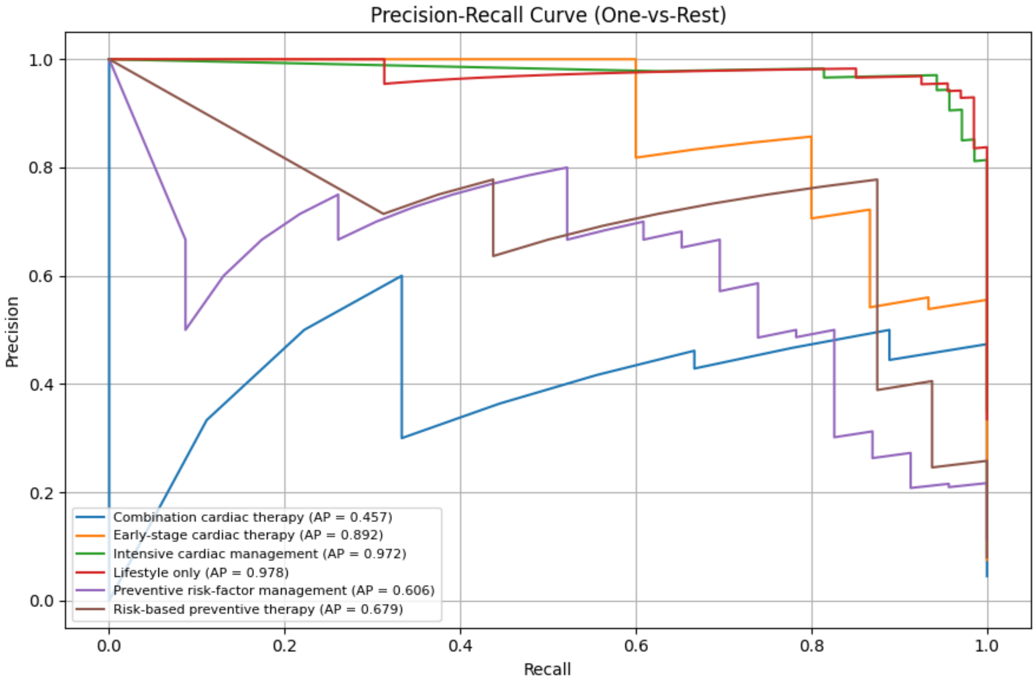

Figure 6: Precision–Recall Analysis for Heart Disease Treatment Prediction

The two-dimensional projection of the dataset using Principal Component Analysis (PCA) is presented in Figure 7. PCA is a dimensionality reduction technique that transforms high-dimensional data into a lower-dimensional space while preserving the maximum variance. In this study, PCA is used to visualize the structure and distribution of patient data across the principal components. As shown in the figure, the samples exhibit distinguishable patterns across different regions of the feature space, indicating a reasonable level of separability among treatment categories. This visualization provides insight into the underlying data structure and supports the effectiveness of the selected features for classification.

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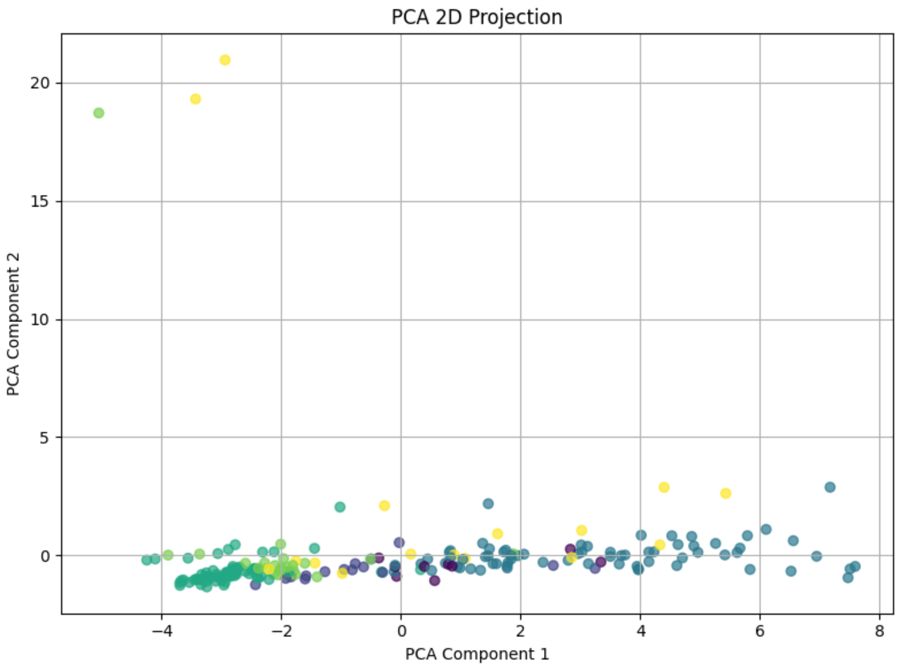

Figure 7: PCA Visualization of Patient Data for Heart Disease Treatment Planning

The most influential features contributing to the model's decision-making process are presented in Figure 8. Feature importance is calculated based on each variable's contribution to the model's predictive outcomes. As shown in the figure, several clinical and lifestyle variables significantly affect treatment prediction. Features related to medical history, lifestyle factors, and key clinical indicators appear to play a dominant role in determining personalized treatment strategies. This analysis provides valuable insight into which patient attributes most strongly influence model predictions and supports the interpretability of the machine learning approach.

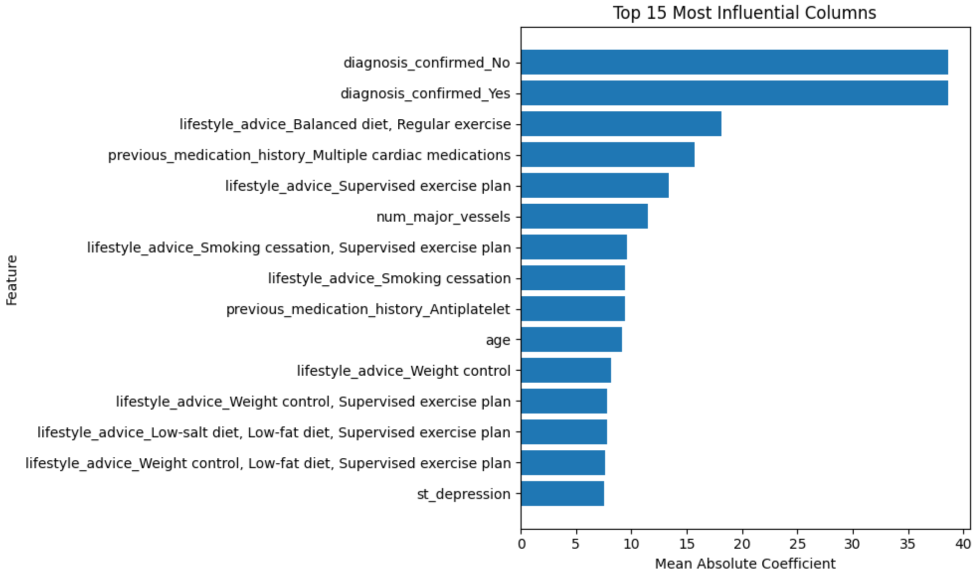

Figure 8: Key Features Influencing Heart Disease Treatment Prediction

Overall, the experimental results indicate that the proposed machine learning approach is effective for predicting personalized treatment categories for heart disease patients.

4.4. Limitations of AI-Based Treatment Planning Models

The analysis of accuracy, loss trends, ROC curves, and precision–recall curves confirms the model's reliability and stability in handling the dataset. In addition, the feature importance analysis highlights key clinical and lifestyle factors that significantly influence treatment prediction, providing insight into the model's decision-making process. These findings demonstrate the potential of machine learning techniques to support data-driven, personalized treatment planning in healthcare systems. Furthermore, the proposed approach has practical implications, as it can assist healthcare professionals in identifying appropriate treatment strategies based on patient-specific clinical and lifestyle attributes. The developed model can serve as a decision-support tool to support more accurate and timely treatment recommendations. In real-world healthcare environments, such systems may reduce diagnostic workload, improve treatment accuracy, and enable early intervention for high-risk patients. Additionally, understanding influential features can help medical practitioners better identify the key factors that affect treatment decisions, thereby enhancing clinical decision-making and promoting more efficient, personalized patient care.

5. Discussion

The results of this study show that machine learning models can effectively support heart disease prediction and personalized treatment planning. Logistic Regression achieved the best performance, followed by XGBoost, Random Forest, and SVM. These findings indicate that machine learning algorithms can successfully analyze clinical data and identify cardiovascular risk patterns. Previous studies also report that machine learning improves disease detection and clinical decision-making by analyzing large healthcare datasets such as electronic health records and wearable device data (Domadiya, 2024; Rani et al., 2025). In addition, machine learning-based recommendation systems can provide personalized medical advice and improve disease prediction accuracy(Hassan & Elagamy, 2025). AI technologies have also shown strong potential in cardiovascular healthcare by improving early diagnosis, risk prediction, and personalized treatment planning (Udoy & Hassan, 2025). Similarly, AI-driven predictive analytics and clinical decision support systems can assist physicians in developing more effective cardiac care strategies (Hassan Tanveer, 2024). Machine learning models such as logistic Regression and random forests have also been widely used for heart disease risk prediction using clinical variables (Liza et al., 2025). Overall, the findings confirm that machine learning can improve heart disease prediction and support data-driven healthcare systems.

6. Findings

This study evaluates machine learning models for predicting personalized treatment strategies for heart disease patients based on clinical data.

1. Logistic Regression showed the best performance, achieving an accuracy of 87% in predicting medication categories.
2. XGBoost achieved 82% accuracy, demonstrating strong capability in treatment classification.
3. Random Forest produced 80% accuracy, confirming the effectiveness of ensemble learning methods.

7. Recommendations

1. Healthcare institutions should consider using machine-learning–based decision-support systems to assist with treatment planning.

2. Future research should use larger real-world clinical datasets to improve prediction accuracy.
3. Researchers may explore advanced algorithms, such as deep learning, to improve treatment prediction.
4. Integration with electronic health record (EHR) systems could support real-time clinical decision making.

8. Limitations

1. Although this study uses clinically verified, real-world data, the sample size of 1,000 patient records may limit its ability to represent the diverse cardiovascular profiles across different global populations fully.
2. The study relied on a specific set of clinical and demographic features. It excluded other parameters, such as genetic data or detailed medical history, which might have influenced overall prediction performance.
3. Only four machine learning classification models were evaluated in this research, meaning that other advanced algorithms, such as deep learning or ensemble methods, not covered here, could potentially yield different results.

9. Conclusion

This study investigated the use of machine learning techniques for predicting personalized treatment strategies for heart disease patients. Using a clinically verified dataset of 1,000 patient records containing demographic and clinical features such as age, gender, blood pressure, and cholesterol level, several machine learning models were evaluated to determine their effectiveness in treatment classification. The results demonstrate that machine learning models can successfully analyze patient health indicators and support treatment decision-making in healthcare systems. Among the evaluated algorithms, Logistic Regression achieved the highest predictive performance with an accuracy of 87%, followed by XGBoost (82%), Random Forest (80%), and Support Vector Machine (79%). These findings suggest that machine learning techniques can identify patterns within clinical data and provide reliable predictions for personalized treatment planning. Overall, the study highlights the potential of machine learning–based decision-support systems to help healthcare professionals make more accurate, data-driven treatment decisions. By analyzing patient characteristics and predicting appropriate treatment categories, such systems can significantly improve personalized healthcare services. For future research, expanding the scope with even larger multi-center clinical datasets will further enhance model reliability and clinical generalizability. Future studies may also incorporate additional clinical variables and explore advanced deep learning approaches to refine predictive performance further and support more effective healthcare decision-making systems.

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