A Mini Project Report

On

SMART HEALTH: ADVANCED HEART DISEASE PREDICTION USING MACHINE LEARNING

Submitted by

1. Saad Bashir Inamdar (59)

2. Arshad Abdulmajeed Perampalli (65)

Under Guidance of

Prof. A. S Adhatrao

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Artificial Intelligence & Data Science Engineering

Pradnya Niketan Education Society, Pune.

NAGESH KARAJAGI *ORCHID* COLLEGE OF ENGINEERING & TECHNOLOGY

SOLAPUR.

2024-2025

Guide **DPAC Member** **HOD**

Pradnya Niketan Education Society , Pune.
NAGESH KARAJAGI *ORCHID* COLLEGE OF ENGG. & TECH., SOLAPUR.

Gut No. 16, Solapur-Tuljapur Road, Tale Hipparaga, Solapur – 413 002
Phone: (0217) 2735001/02, Fax. (0217) 2735004

Certificate

This is to certify that **Mr. SAAD BASHIR INAMDAR** of class TY(AI&DS) Roll No. 59 has satisfactorily completed the Mini Project work entitled **"SMART HEALTH: ADVANCED HEART DISEASE PREDICTION USING MACHINE LEARNING"** as Prescribed by Dr. Babasaheb Ambedkar Technological University Lonere, Maharashtra, India in the academic year 2024-25.

Date of Submission:

(Prof. A. S Adhatrao)	(Dr M. B. Patil)
Mini Project Guide	**Head of Department**

Examiners: (Name with Signature & Date)

1 : ____

2 : ____

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Phone: (0217) 2735001/02, Fax. (0217) 2735004

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This is to certify that **Mr.ARSHAD ABDULMAJEED PERAMPALLI** of class TY(AI&DS) Roll No. 65 has satisfactorily completed the Mini Project work entitled **"SMART HEALTH: ADVANCED HEART DISEASE PREDICTION USING MACHINE LEARNING"** as Prescribed by Dr. Babasaheb Ambedkar Technological University Lonere, Maharashtra, India in the academic year 2024-25.

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(Dr M. B. Patil)
Head of Department

Examiners: (Name with Signature & Date)

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2 : ____

ABSTRACT

Heart disease is a major global health concern and a leading cause of death, emphasizing the critical need for early detection and prevention strategies. Machine learning techniques, particularly logistic regression, provide effective tools for predicting heart disease by analyzing clinical and demographic data. Logistic regression is a widely used and interpretable classification algorithm that models the relationship between risk factors and the likelihood of heart disease.

This study explores the application of logistic regression for heart disease prediction using a dataset that includes key features such as age, cholesterol levels, blood pressure, glucose levels, and lifestyle habits. The model is trained and evaluated on preprocessed data, with feature selection methods employed to identify significant predictors. Performance metrics, including accuracy, precision, recall, and the area under the receiver operating characteristic (ROC) curve, are calculated to assess the model's effectiveness.

The results demonstrate that logistic regression performs well in predicting heart disease, providing accurate and interpretable insights into the role of various risk factors. Its simplicity and efficiency make it a valuable tool for clinical decision-making. This study highlights the potential of logistic regression to enhance early diagnosis, optimize resource allocation, and improve patient outcomes in heart disease prevention and management.

ACKNOWLEDGEMENT

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Date: **Student's Names:** **Sign**

1. Saad Bashir Inamdar (59):

2. Arshad Abdulmajeed perampalli (65):

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CHAPTER I
INTRODUCTION

Heart disease is a critical global health issue, accounting for millions of deaths annually and imposing a significant burden on healthcare systems. Early detection and prevention are key strategies to reduce the prevalence and impact of heart disease. Traditional diagnostic approaches, while effective, often involve extensive testing, specialized expertise, and significant time and cost investments. In this context, machine learning (ML) has emerged as a transformative tool, offering efficient and accurate methods for disease prediction by uncovering patterns in complex medical data.

Among various ML techniques, logistic regression is particularly well-suited for heart disease prediction due to its simplicity, interpretability, and effectiveness in binary classification tasks. Logistic regression models the relationship between input features and the probability of an outcome, making it ideal for predicting the presence or absence of a condition. In the context of heart disease, it can analyze key features such as age, cholesterol levels, blood pressure, blood sugar levels, and lifestyle habits to estimate disease risk.

This study focuses on applying logistic regression to heart disease prediction using a publicly available dataset containing clinical and demographic information. The model is developed and evaluated using performance metrics such as accuracy, precision, recall, and the area under the receiver operating characteristic (ROC) curve. Additionally, feature importance analysis highlights the relative contribution of different risk factors, offering valuable insights for clinicians.

By providing an interpretable and efficient prediction framework, this study aims to demonstrate the utility of logistic regression in heart disease diagnosis and risk assessment. The findings can aid healthcare professionals in identifying high-risk individuals early, enabling timely interventions and optimizing resource allocation, ultimately contributing to improved patient outcomes and preventive care strategies.

CHAPTER II
LITERATURE REVIEW

The growing prevalence of heart disease has motivated researchers to explore machine learning (ML) techniques for early diagnosis and prevention. Logistic regression, a widely used and interpretable ML algorithm, has emerged as an effective method for heart disease prediction due to its simplicity, efficiency, and ability to model binary outcomes. This section reviews significant studies highlighting the role of logistic regression in predicting heart disease and its integration with other techniques for improved performance.

Logistic regression is valued for its ability to estimate the probability of an outcome based on a set of input variables. Several studies have demonstrated its effectiveness in predicting heart disease. Khare et al. (2020) used logistic regression to analyze clinical features such as blood pressure, cholesterol levels, and blood sugar, achieving over 85% accuracy on widely used datasets. The study emphasized logistic regression's ability to identify critical risk factors, making it an essential tool for medical applications. Similarly, Muhammad et al. (2021) implemented logistic regression combined with recursive feature elimination, showing improved performance through effective feature selection.

Comparative analyses have established logistic regression as a competitive approach in heart disease prediction. Kumar et al. (2022) compared logistic regression with decision trees, support vector machines (SVM), and ensemble methods. While advanced models offered slightly higher accuracy, logistic regression excelled in interpretability and computational efficiency, making it a preferred choice in resource-constrained healthcare settings. Furthermore, studies like Patel et al. (2021) highlighted the importance of transparency in clinical decision-making, which logistic regression provides by showing the contribution of individual features.

The robustness of logistic regression has been enhanced through integration with feature engineering techniques. Methods such as principal component analysis (PCA) and regularization techniques like LASSO have been employed to address multicollinearity and overfitting issues. For instance, Jain et al. (2021) applied logistic regression with LASSO regularization on a heart disease dataset, demonstrating improved model generalization and predictive accuracy. Additionally, including lifestyle and socio-economic factors, such as smoking habits and physical activity levels, has expanded the application of logistic regression beyond traditional clinical data.

Despite its advantages, logistic regression faces challenges when dealing with imbalanced datasets, where the number of positive cases (presence of heart disease) is significantly smaller than negative cases. Studies have addressed this limitation using data balancing techniques such as Synthetic Minority Over-sampling Technique (SMOTE) to improve prediction performance. Gupta et al. (2022) showed that combining logistic regression with SMOTE effectively mitigates class imbalance, ensuring reliable predictions.

Recent advancements also explore hybrid approaches, where logistic regression is combined with other ML algorithms. For instance, ensemble methods like bagging and boosting incorporate logistic regression as a base learner to improve accuracy without compromising interpretability. These hybrid approaches demonstrate that logistic regression remains a valuable component in predictive modeling.

In summary, the literature establishes logistic regression as a reliable and interpretable model for heart disease prediction. Its simplicity, efficiency, and adaptability to various datasets and techniques make it a key tool in advancing preventive healthcare. Future research should focus on integrating logistic regression with more comprehensive datasets and advanced ML techniques to further enhance its predictive power and clinical utility.

CHAPTER III

TECHNOLOGY

The heart disease prediction technology leverages the power of logistic regression, a supervised machine learning algorithm, to analyze clinical and demographic data for identifying individuals at risk. The system is designed with an emphasis on accuracy, interpretability, and scalability, making it suitable for healthcare settings ranging from hospitals to community clinics.

3.1 Data Collection and Preprocessing

Data Sources: The system relies on patient data, including clinical (cholesterol, blood pressure, glucose levels), demographic (age, gender), and lifestyle (smoking, physical activity) attributes. These features are obtained from electronic health records (EHRs) or manually input data.

Preprocessing: The raw data undergoes cleaning, normalization, and encoding of categorical variables to prepare it for analysis. Missing values are handled using imputation techniques, and outliers are addressed to maintain data integrity.

3.2 Feature Selection

The technology integrates feature selection techniques like Recursive Feature Elimination (RFE) or statistical tests to identify the most relevant predictors of heart disease. These features help reduce noise and improve the model's efficiency.

3.3 Logistic Regression Model

Core Algorithm: Logistic regression is employed as the core prediction algorithm. It uses a sigmoid function to output probabilities indicating the likelihood of heart disease based on the selected features.

Model Training: The system trains the logistic regression model on labeled datasets, applying techniques like LASSO regularization to prevent overfitting and enhance generalizability.

3.4 Model Evaluation

The system evaluates model performance using metrics such as accuracy, precision, recall, F1 score, and the area under the ROC curve (AUC-ROC). Cross-validation ensures robustness and reliability.

3.5 Prediction and Decision Support

Risk Scoring: For each patient, the model calculates a risk score indicating the likelihood of heart disease.

Interpretability: Coefficients of the logistic regression model provide insights into the contribution of each feature, aiding clinicians in understanding risk factors.

3.6 User Interface

A user-friendly interface allows healthcare providers to input patient data and view real-time predictions. Visual aids like graphs and heatmaps display risk factors, enhancing decision-making.

3.7 Deployment

Cloud-based or On-Premise: The technology can be deployed as a cloud-based service for scalability or an on-premise application for secure data environments.

Integration: Seamlessly integrates with existing EHR systems and healthcare workflows.

3.8 Future Enhancements

Incorporate real-time data streams from wearable health devices to improve prediction accuracy.

Employ hybrid models combining logistic regression with other machine learning algorithms to enhance performance without sacrificing interpretability.

This technology represents a cost-effective, interpretable, and clinically relevant solution for heart disease prediction, empowering healthcare providers to implement preventive interventions and save lives.

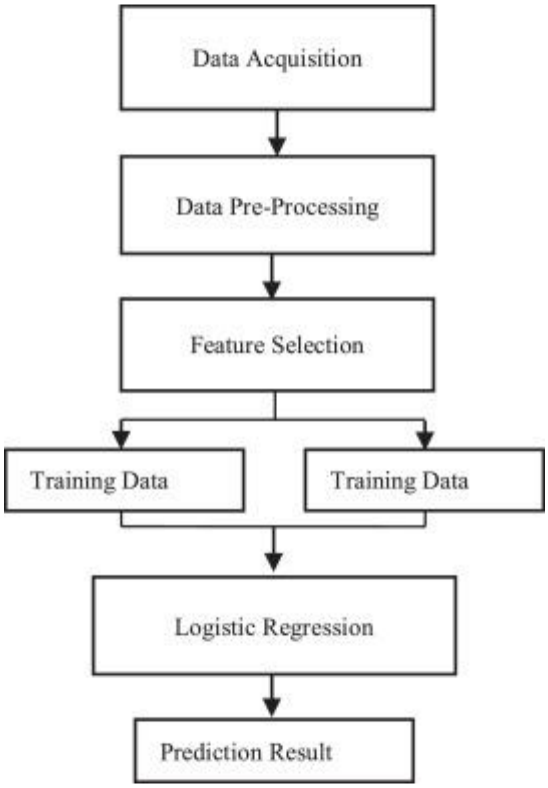


Fig.3.1

CHAPTER IV
ADVANTAGES

This project provides several benefits due to its integration of advanced technologies and user-centric design. Below are the key advantages, numbered for clarity:

4.1 Simplicity and Interpretability: Logistic regression is straightforward to implement and interpret, making it an ideal choice for medical applications where understanding the influence of risk factors is crucial. Clinicians can easily comprehend how each feature contributes to heart disease risk, facilitating informed decision-making.

4.2 Efficiency with Binary Classification: Logistic regression is specifically designed for binary classification tasks, such as predicting the presence or absence of heart disease. It efficiently models the probability of an outcome, providing clear and actionable results.

4.3 Low Computational Requirements: Compared to complex machine learning algorithms, logistic regression requires fewer computational resources. This makes it suitable for deployment in resource-constrained environments, such as small clinics or remote healthcare facilities.

4.4 Feature Importance Insights: Logistic regression provides coefficients that indicate the importance of each feature in predicting the outcome. This helps identify key risk factors, such as high blood pressure or cholesterol levels, enabling targeted prevention strategies.

4.5 Flexibility with Feature Engineering: The algorithm works well with engineered features, allowing the inclusion of clinical, demographic, and lifestyle variables. Techniques like one-hot encoding for categorical data and normalization for continuous data enhance its performance.

4.6 Robustness Against Overfitting: Regularization techniques like LASSO (L1) or Ridge (L2) can be applied to logistic regression models to reduce overfitting, ensuring better generalization to new data.

4.7 Compatibility with Small and Medium-Sized Datasets: Logistic regression performs effectively on small to medium-sized datasets, which are common in medical studies, reducing the need for large-scale data collection.

4.8 Ease of Implementation and Deployment: Logistic regression is widely supported by machine learning libraries (e.g., Scikit-learn, TensorFlow), making it easy to implement. Its lightweight nature also simplifies deployment in cloud or on-premise healthcare systems.

4.9 Good Baseline Performance: Logistic regression often serves as a strong baseline model. Its predictive power is competitive with more complex algorithms, especially in structured data scenarios like heart disease prediction.

4.10 Transparency in Decision-Making: Transparency is critical in healthcare. Logistic regression provides clear probabilities and thresholds for decision-making, ensuring clinicians can justify their diagnoses and treatments.

4.11 Versatility Across Domains: Logistic regression can handle a variety of data types, from clinical measurements to socio-economic and lifestyle factors, making it a versatile choice for heart disease prediction models.

4.12 Support for Balanced and Imbalanced Datasets: Techniques like Synthetic Minority Oversampling Technique (SMOTE) can be used with logistic regression to handle class imbalance, ensuring accurate predictions even when heart disease cases are underrepresented.

4.13 Scalability with Hybrid Approaches: Logistic regression can be combined with other machine learning models in ensemble or hybrid frameworks, boosting accuracy while retaining interpretability.

Logistic regression offers an efficient, interpretable, and flexible solution for heart disease prediction, making it highly valuable in clinical applications. Its ability to balance simplicity with effectiveness ensures it remains a trusted tool in machine learning-driven healthcare.

CHAPTER V
DISADVANTAGES

While this project is innovative and useful, it also has several limitations and challenges that affect its overall functionality. Below are the main disadvantages, numbered for clarity:

5.1 Linear Decision Boundary: Logistic regression assumes a linear relationship between the features and the log-odds of the outcome. This limitation means it may struggle to model complex, non-linear relationships in heart disease data, which can lead to reduced predictive accuracy compared to more advanced algorithms like neural networks or random forests.

5.2 Sensitivity to Feature Scaling: Logistic regression is sensitive to differences in feature scaling. Features with larger ranges can dominate the model unless properly normalized or standardized, requiring additional preprocessing steps.

5.3 Limited Handling of Non-linearity: Without transformation or feature engineering, logistic regression cannot inherently model interactions or non-linear dependencies between features. This makes it less suitable for datasets where such relationships are significant.

5.4 Performance on High-Dimensional Data: In datasets with a large number of features, logistic regression can be prone to overfitting, especially if the sample size is small. While regularization techniques like LASSO and Ridge help, they may not always address the limitations effectively.

5.5 Vulnerability to Multicollinearity: Logistic regression is sensitive to multicollinearity, where highly correlated features can distort the model's coefficient estimates. This requires additional effort in feature selection or dimensionality reduction.

5.6 Imbalanced Dataset Challenges: Logistic regression may perform poorly on imbalanced datasets where one class (e.g., "no heart disease") dominates. Without techniques like oversampling, undersampling, or adjusted class weights, the model may produce biased predictions.

5.7 Dependence on Relevant Features: Logistic regression relies heavily on the relevance of input features. Poorly chosen or incomplete features can significantly degrade model performance, requiring robust feature selection and domain expertise.

5.8 Susceptibility to Overfitting with Noisy Data: In the presence of noisy or irrelevant data, logistic regression can overfit, capturing random patterns instead of true relationships, leading to poor generalization on unseen data.

5.9 Difficulty Handling Categorical Variables: While logistic regression supports categorical variables, they need to be transformed (e.g., one-hot encoding), which can increase feature dimensionality and complicate model interpretation.

5.10 Limited Scalability for Large Datasets: Logistic regression may struggle with very large datasets, as the optimization process can become computationally intensive, particularly if advanced regularization techniques are used.

5.11 Assumes Independence of Observations: Logistic regression assumes that observations are independent of one another. In cases where data points are correlated (e.g., repeated measures or grouped data), the model's predictions may be inaccurate.

5.12 Low Adaptability to Changing Data: Logistic regression is less adaptable to dynamic or evolving datasets compared to algorithms like decision trees, which can be updated incrementally.

5.13 Compromised Performance with Limited Data Although logistic regression can handle small datasets, it requires sufficient data to estimate coefficients accurately. With limited data, the model may produce unreliable results.

While logistic regression offers simplicity and interpretability, it has limitations in handling complex, non-linear, or high-dimensional data. Addressing these challenges often requires additional preprocessing, feature engineering, or hybrid approaches, which can reduce its simplicity advantage.

CHAPTER VI
APPLICATIONS

6.1 Early Detection of Heart Disease: Logistic regression is widely used in healthcare systems to predict the likelihood of heart disease in patients based on clinical, demographic, and lifestyle data. By identifying individuals at high risk, clinicians can intervene early with preventive measures, such as medication, lifestyle changes, or further diagnostic tests, reducing the overall burden of cardiovascular diseases.

6.2 Risk Stratification for Personalized Treatment Plans: Heart disease risk prediction using logistic regression helps classify patients into different risk categories (e.g., low, moderate, high risk). This stratification allows healthcare providers to personalize treatment plans, tailoring interventions based on individual risk profiles. For instance, high-risk individuals may receive more aggressive treatments, while low-risk patients may focus on prevention through lifestyle modification.

6.3 Clinical Decision Support Systems (CDSS): Logistic regression models can be integrated into clinical decision support systems to aid healthcare professionals in diagnosing heart disease. By providing real-time predictions, the system supports clinicians in making informed decisions on patient care, enhancing diagnostic accuracy and efficiency.

6.4 Public Health Surveillance and Risk Assessment: Governments and health organizations can use logistic regression models to analyze population-level data and identify trends in heart disease prevalence. By predicting risk in large populations, policymakers can allocate resources more effectively, implement targeted prevention programs, and address public health issues associated with cardiovascular diseases.

6.5 Predictive Modeling in Electronic Health Records (EHR) Systems: Logistic regression can be incorporated into electronic health record systems to automatically analyze patient data for heart disease prediction. This integration helps clinicians quickly assess a patient's risk, leading to more timely interventions and better patient outcomes. It also reduces the burden on healthcare professionals by automating the risk assessment process.

6.6 Telemedicine and Remote Patient Monitoring: With the rise of telemedicine and wearable health devices, logistic regression models can be used to predict heart disease risk remotely. Data collected from wearable devices, such as heart rate, blood pressure, and activity levels, can be input into the model, allowing for continuous monitoring and early warning of potential cardiovascular issues.

6.7 Health Risk Assessments for Insurance Providers: Insurance companies can use logistic regression to assess heart disease risk as part of health underwriting processes. By incorporating clinical data, lifestyle factors, and demographic information, insurers can better understand the health risks of applicants and offer personalized premiums based on predicted heart disease risk.

6.8 Drug Development and Clinical Trials: Logistic regression models can assist in the identification of key biomarkers or risk factors for heart disease, supporting pharmaceutical companies in drug development. By predicting which patients are more likely to benefit from certain treatments, logistic regression can help streamline clinical trials, improving the efficiency and effectiveness of testing new cardiovascular drugs.

6.9 Emergency Medical Services (EMS) Triage: Logistic regression can be used in emergency medical services to predict the likelihood of a heart attack or other cardiovascular events in patients based on their symptoms and clinical data. EMS can prioritize high-risk patients for immediate treatment, improving response times and outcomes in critical situations.

6.10 Healthcare Chatbots and Virtual Assistants: Logistic regression can power predictive algorithms within healthcare chatbots or virtual assistants. These systems can collect symptom data and provide immediate risk assessments for heart disease, offering recommendations for follow-up consultations or lifestyle modifications based on predicted risk.

Logistic regression is a versatile tool in heart disease prediction, with applications across various sectors of healthcare, from early detection and risk stratification to personalized treatment and public health management. Its simplicity, interpretability, and ability to handle structured medical data make it a valuable asset in enhancing patient outcomes, optimizing resource allocation, and improving overall healthcare delivery.

CHAPTER VII
FUTURE SCOPE

The future scope of heart disease prediction using logistic regression in machine learning is promising, as advancements in data collection, algorithm development, and healthcare infrastructure will significantly enhance its capabilities and applicability. Here are some key areas for growth and innovation:

7.1 Integration with Real-Time Data

Wearable Devices and IoT: The proliferation of wearable health devices (e.g., smartwatches, fitness trackers) and Internet of Things (IoT) sensors can provide real-time health data such as heart rate, ECG, blood pressure, and oxygen levels. Logistic regression models can be enhanced to predict heart disease risks dynamically by continuously analyzing this real-time data, leading to proactive healthcare and continuous monitoring.

Personalized Health Tracking: With continuous monitoring, heart disease risk assessments can become more personalized. Logistic regression models can incorporate real-time data from wearables to offer more accurate predictions of sudden changes in health, such as heart attacks, allowing for immediate intervention.

7.2 Hybrid Models for Improved Performance

Combining Logistic Regression with Other Techniques: While logistic regression is effective, combining it with other machine learning algorithms like Random Forest, Support Vector Machines (SVM), or deep learning can lead to hybrid models that enhance prediction accuracy. For example, ensemble models or stacked models could use logistic regression as one component, helping improve overall performance in complex datasets.

Model Tuning and Optimization: The use of techniques such as grid search, cross-validation, and hyperparameter tuning can further refine logistic regression models, enhancing their ability to handle diverse datasets and improving generalization.

7.3 Handling High-Dimensional Data

Big Data Integration: With the availability of large-scale medical data, logistic regression models can be expanded to handle big data efficiently. Advanced dimensionality reduction methods like PCA (Principal Component Analysis) and feature engineering will enable logistic regression to effectively process complex, high-dimensional medical data without sacrificing performance.

7.4 Explainability and Transparency in AI

Improved Interpretability: One of the key advantages of logistic regression is its interpretability. In the future, there will be more focus on improving the transparency of predictive models, particularly in healthcare settings.

Post-Hoc Explanations: Tools like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) can be integrated with logistic regression models to enhance explainability by showing the influence of each feature on individual predictions.

7.5 Increased Accuracy with Advanced Regularization

Advanced Regularization Techniques: Future advancements in regularization methods such as Elastic Net or automatic feature selection will further reduce overfitting and improve the performance of logistic regression in heart disease prediction. These techniques can help the model focus on the most relevant features and ignore noise, leading to more accurate predictions on new or unseen data.

7.6 Incorporation of Lifestyle and Social Determinants

Incorporating Non-Clinical Factors: Beyond clinical data, incorporating lifestyle and social determinants of health (e.g., income level, education, environment, psychological stress) will lead to more holistic heart disease risk predictions. Logistic regression models could be adapted to include these factors, enabling predictions that reflect the complex, multifaceted nature of heart disease risk.

Personalized Prevention and Treatment: Logistic regression could predict not just the likelihood of heart disease but also suggest personalized preventive measures or treatment plans based on the patient's full risk profile, including their lifestyle factors.

7.7 Collaborative Healthcare Systems

Integration with Health Records: Logistic regression models can be further integrated with Electronic Health Record (EHR) systems, allowing for seamless and automatic risk assessments in healthcare workflows. This integration will lead to better patient management and the ability to provide immediate recommendations for interventions.

Cross-Institutional Data Sharing: As more healthcare organizations adopt machine learning tools, future logistic regression models may benefit from cross-institutional data sharing. This could improve model training on diverse datasets, allowing for more generalized and robust predictions, especially in global health applications.

7.8 Addressing Data Imbalance

Better Handling of Imbalanced Datasets: Future advancements will likely improve logistic regression's ability to handle imbalanced datasets, which is common in heart disease prediction due to the relative scarcity of patients with heart disease. Techniques like Synthetic Minority Over-sampling Technique (SMOTE) or class-weighted models will enhance the model's ability to accurately predict heart disease in low-incidence populations.

7.9 Global Health and Accessibility

Wider Adoption in Low-Resource Settings: Logistic regression models, being relatively simple and computationally efficient, are ideal for deployment in low-resource settings, especially in developing countries. Future applications could involve creating accessible heart disease prediction tools for regions with limited healthcare infrastructure, leveraging mobile platforms or low-cost healthcare systems.

Global Health Monitoring: By integrating logistic regression into global health monitoring systems, healthcare organizations can predict trends in cardiovascular health on a larger scale, enabling better resource allocation and more effective public health policies.

The future of heart disease prediction using logistic regression in machine learning lies in the continued enhancement of model performance, interpretability, and accessibility. With the integration of real-time data, hybrid modeling techniques, personalized treatment recommendations, and the inclusion of non-clinical factors, logistic regression will continue to be a crucial tool in both individual patient care and global healthcare initiatives. As these advancements unfold, logistic regression will play a key role in improving heart disease prevention, diagnosis, and treatment strategies.

CHAPTER VIII
CONCLUSION

Heart disease prediction using logistic regression in machine learning represents a powerful and practical approach for improving cardiovascular healthcare. The simplicity, interpretability, and effectiveness of logistic regression make it an excellent tool for predicting heart disease risk based on clinical, demographic, and lifestyle factors. By leveraging patient data, logistic regression models can provide early warnings, enabling healthcare providers to take preventive actions and develop personalized treatment plans that improve patient outcomes.

Despite its advantages, such as ease of implementation and robust performance with smaller datasets, logistic regression has some limitations, including its assumption of linear relationships and sensitivity to multicollinearity. However, with proper feature selection, regularization, and data preprocessing, these limitations can be mitigated, making logistic regression an even more powerful tool in heart disease prediction.

As healthcare systems continue to evolve with the advent of wearable devices, real-time data streams, and large-scale health data, logistic regression models will play an increasingly important role in both individual patient care and population-level health management. Future advancements in hybrid modeling, integration with electronic health records, and better handling of complex, multidimensional data will further enhance the effectiveness of heart disease prediction systems.
In conclusion, logistic regression offers an accessible, interpretable, and efficient approach to predicting heart disease, with the potential to improve preventive care, reduce healthcare costs, and ultimately save lives. With continued advancements in machine learning, this technology will play a vital role in shaping the future of cardiovascular health management.

CHAPTER IX

RESULTS

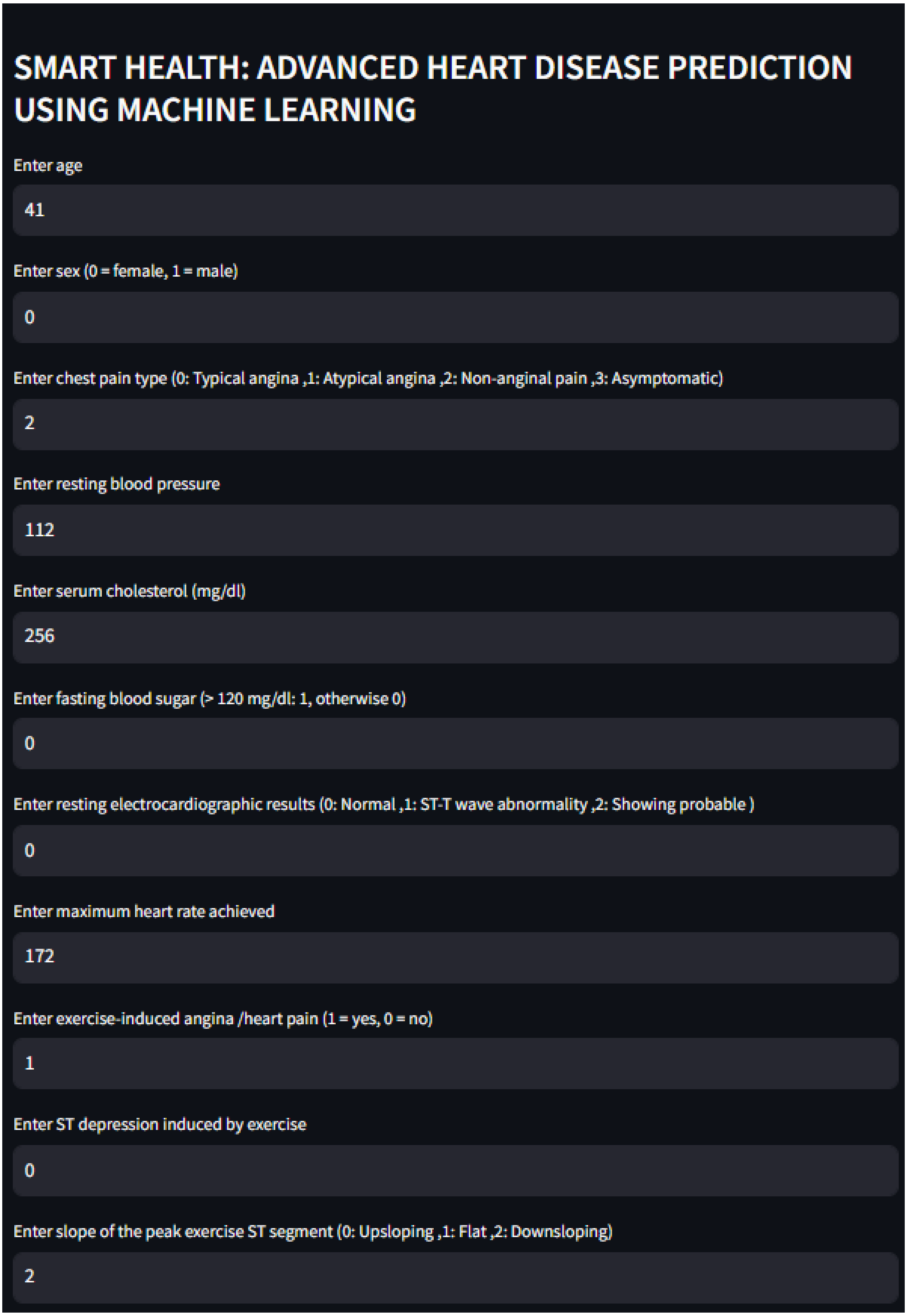
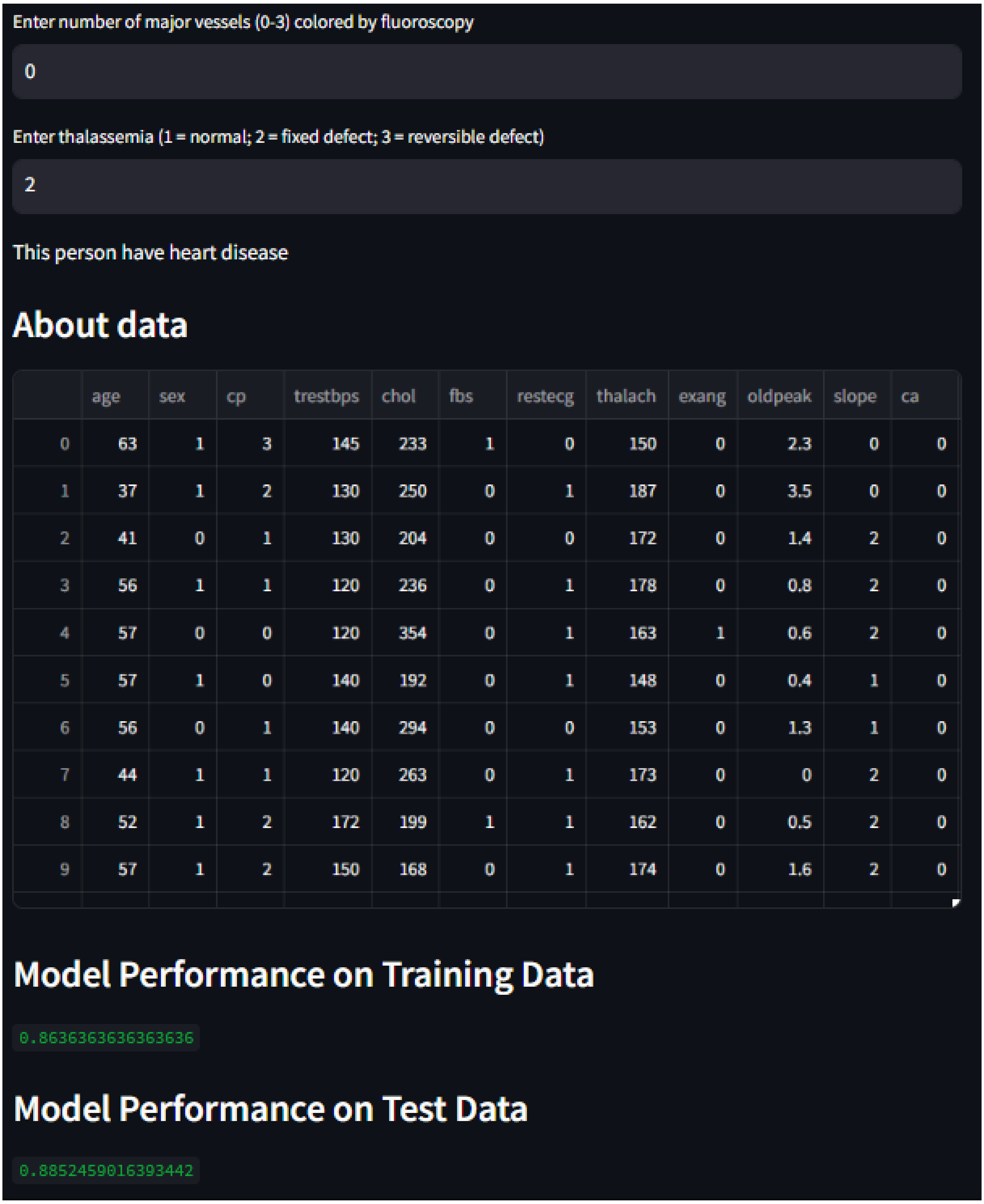


Fig.9.1



Enter number of major vessels (0-3) colored by fluoroscopy

0

Enter thalassemia (1 = normal; 2 = fixed defect; 3 = reversible defect)

2

This person have heart disease

About data

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca
0	63	1	3	145	233	1	0	150	0	2.3	0	0
1	37	1	2	130	250	0	1	187	0	3.5	0	0
2	41	0	1	130	204	0	0	172	0	1.4	2	0
3	56	1	1	120	236	0	1	178	0	0.8	2	0
4	57	0	0	120	354	0	1	163	1	0.6	2	0
5	57	1	0	140	192	0	1	148	0	0.4	1	0
6	56	0	1	140	294	0	0	153	0	1.3	1	0
7	44	1	1	120	263	0	1	173	0	0	2	0
8	52	1	2	172	199	1	1	162	0	0.5	2	0
9	57	1	2	150	168	0	1	174	0	1.6	2	0

Model Performance on Training Data

`0.8636363636363636`

Model Performance on Test Data

`0.8852459016393442`

Fig 9.2

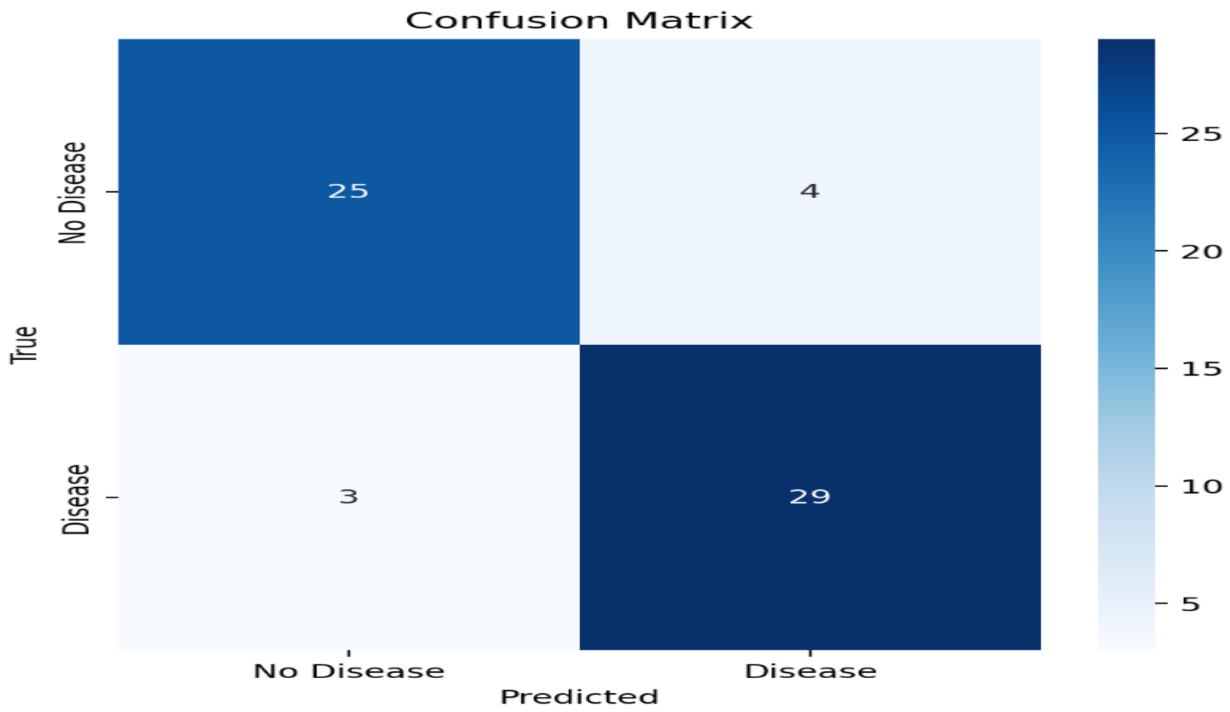

Confusion Matrix
No Disease
Disease
True
25
4
3
29
25
20
15
10
5
No Disease
Disease
Predicted

Fig.9.3

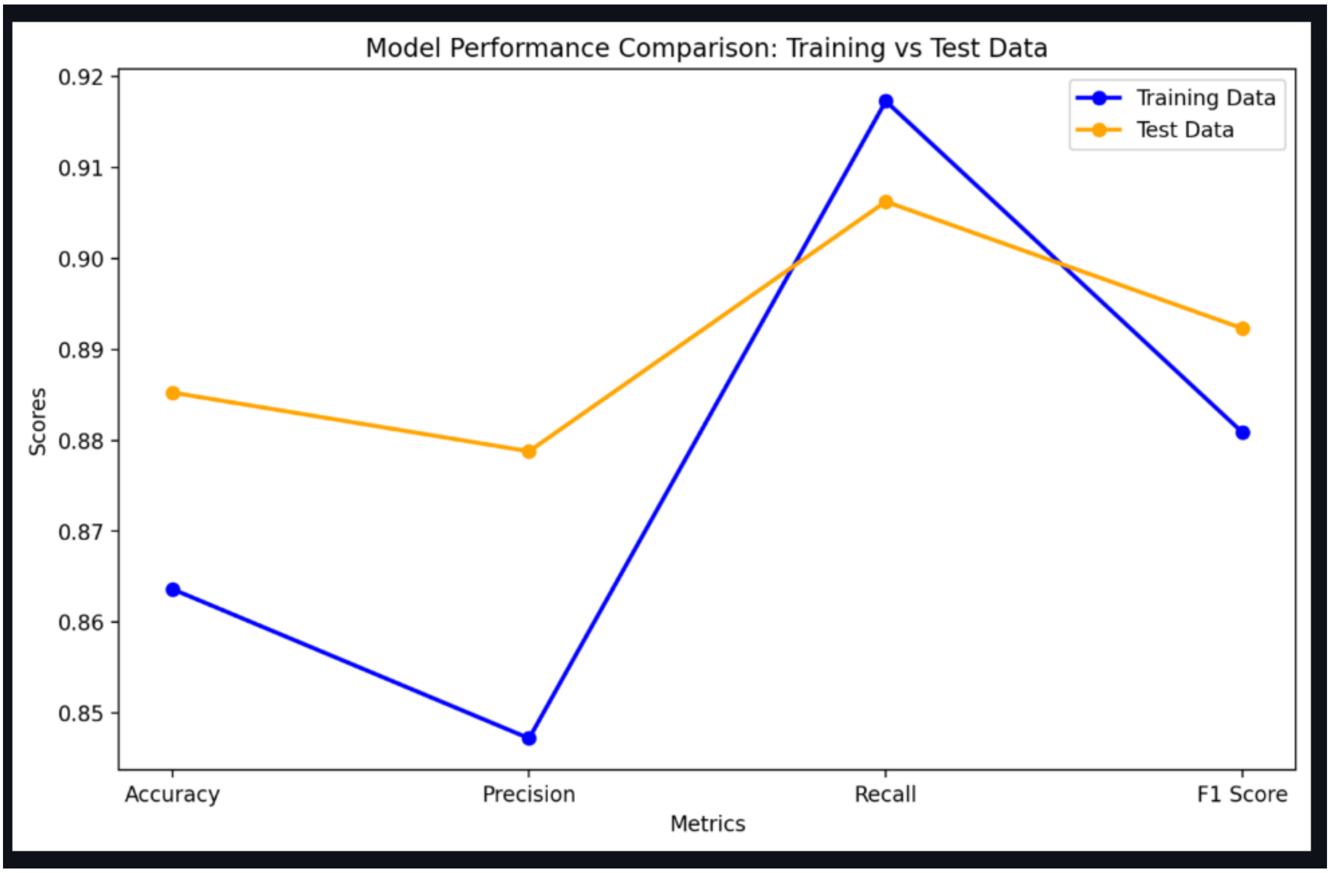

Model Performance Comparison: Training vs Test Data
0.92
0.91
0.90
0.89
0.88
0.87
0.86
0.85
Scores
Training Data
Test Data
Accuracy
Precision
Recall
F1 Score
Metrics

Fig.9.4

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