IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Heart Disease Prediction Using Machine Learning

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Abstract: The objective of this study is to develop a robust machine learning pipeline for heart disease prediction using an ensemble of K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), and Decision Tree (DT) models, with hyperparameter tuning to improve accuracy. Early and precise detection of heart disease is vital in the medical field for better treatment outcomes. The process begins with importing necessary libraries and loading the dataset, followed by data preprocessing, which includes exploratory data analysis, handling missing values, reducing memory usage, and describing features. Outliers are identified using boxplots to ensure data quality. Visualization is carried out through univariate and bivariate analysis using scatter plots to explore relationships between features such as age, chest pain, and exercise. After applying MinMax scaling, the data is split into training and test sets. The models are then built and optimized using hyperparameter tuning. Finally, performance is evaluated using accuracy and classification reports, with a comparison of the models to determine the most effective one. This complete pipeline offers a scalable and accurate solution for heart disease diagnosis.

***Index Terms*- Heart Disease Prediction, Machine Learning, KNN, SVM, Decision Tree, Hyperparameter Tuning, Medical Diagnosis, Classification Models, Health Informatics, Predictive Analytics.**

I. INTRODUCTION

Heart disease is a leading cause of global mortality, with traditional diagnostic methods being time-consuming and prone to errors. Machine learning (ML) offers a promising alternative by analyzing large datasets to improve diagnostic accuracy. Ensemble learning methods combining models like K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), and Decision Trees (DT) can further enhance prediction performance. Hyperparameter tuning optimizes these models for better accuracy. Data preprocessing is essential for accurate predictions, including handling missing values, scaling features, and splitting data into training and test sets. KNN, SVC, and DT each have unique strengths: KNN is simple and effective, SVC handles high-dimensional data well, and DT is interpretable, making it suitable for medical applications. This research aims to build a machine learning system to assist healthcare professionals in diagnosing heart disease more efficiently, leading to better treatment outcomes and reduced global mortality.

1.1 Problem Statement

Cardiovascular diseases are the leading cause of death worldwide, exacerbated by unhealthy habits. Traditional diagnostic methods like ECG and stress tests are costly and require expertise, delaying early detection. Machine learning can enhance diagnosis by analyzing patient data, speeding up and improving accuracy. This study uses KNN, SVC, and DT models, combined through ensemble learning, to predict heart disease. Proper data preprocessing and hyperparameter tuning ensure the models perform optimally. The aim is to develop a reliable system that helps healthcare professionals make quicker, more accurate decisions.

1.2 Use of Algorithms

ML algorithms handle complex healthcare data more efficiently than traditional methods. This project uses KNN, SVC, and DT, each excelling in different areas: KNN for simplicity, SVC for high-dimensional data, and DT for interpretability. Ensemble learning improves the models' accuracy by combining their strengths.

1.3 Benefits of Algorithms

KNN is simple, interpretable, and effective with both numerical and categorical data. SVC excels at handling complex, non-linear data, and Decision Trees provide transparency, making it easy for doctors to follow. These models, when combined through ensemble learning, offer enhanced accuracy for heart disease prediction.

II. DATA DESCRIPTION

We used the data from the Cleveland heart data set from the UCI machine learning repository. The data we selected is made up of 14 variables and 303 in-stances. Overall speaking, there are 13 variables and 1 categorical response variables (target). Among these variables, numerical variables are age, trtbps, chol, thalach, old peak; Categorical variables are sex, exang, cp, fbs, rest_ecg, slp, thall, target. The table below illuminates the meaning of each variable. Detailed information could be seen in **Table 1.**

Table 1. Variable description

Variable	Description	Range/Values
Age	Age of the patient	29 - 77
Sex	Sex of the patient	0 = Female, 1 = Male
exang	Exercise induced angina	0 = No, 1 = Yes
cp	Chest pain type	1 = Typical, 2 = Atypical, 3 = Non-anginal, 4=Asymptomatic
trtbps	Resting blood pressure (mm Hg)	94 - 200
chol	Cholesterol (mg/dl)	126 - 564
fbs	Fasting blood sugar	0=<=120 mg/dl, 1= >120 mg/dl
restecg	Resting ECG results	0 = Normal, 1 = ST-T Abnormality, 2 = LV Hypertrophy
thalach	Max heart rate achieved	71 - 202
oldpeak	ST depression (exercise vs rest)	0 – 6.2
slp	Slope of ST segment	0,1,2
thall	Thalassemia	0 = Null, 1 = Fixed, 2 = Normal, 3 = Reversible
target	Heart attack chance	0 = Less, 1 = More

From **Figure 1**, we see that most patients with high fasting blood sugar (**fbs = 1**) and heart disease are aged **50-70**, peaking around **60 and 69 years**. Patients without heart disease (**fbs = 0**) also fall mostly in this range, with peaks around **56 and 68 years**. Very few cases appear below **40 or above 75 years**. The dataset spans **29-77 years**.

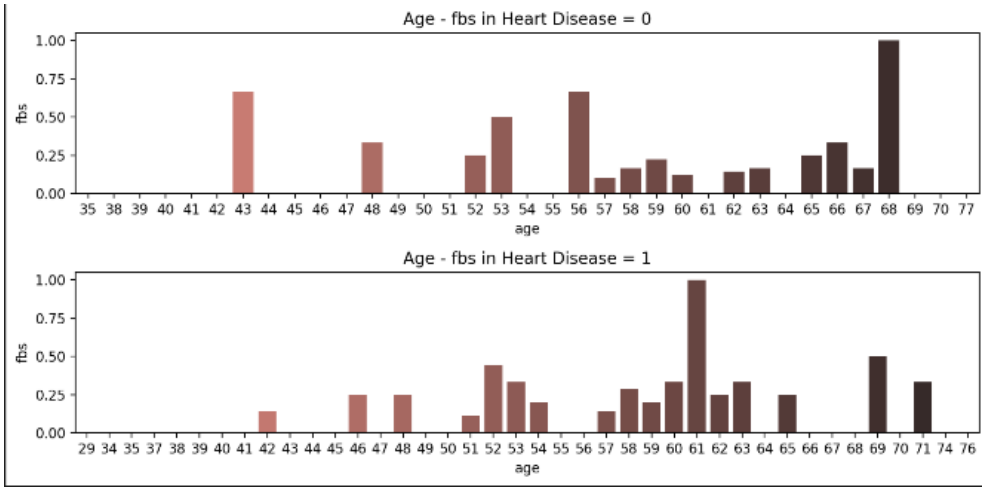

Figure 1. Analysis of Age and Fasting Blood Sugar (fbs) in Individuals with Heart Disease

According to **Figure 2,** It compares age and chest pain type (cp) in patients with and without heart disease. In the top graph (Heart Disease = 0), chest pain occurs less frequently and is scattered across different ages. In the bottom graph (Heart Disease = 1), chest pain is more frequent, especially in the age range of 35 to 70 years. Younger individuals below 40 with chest pain are more likely to have heart disease.

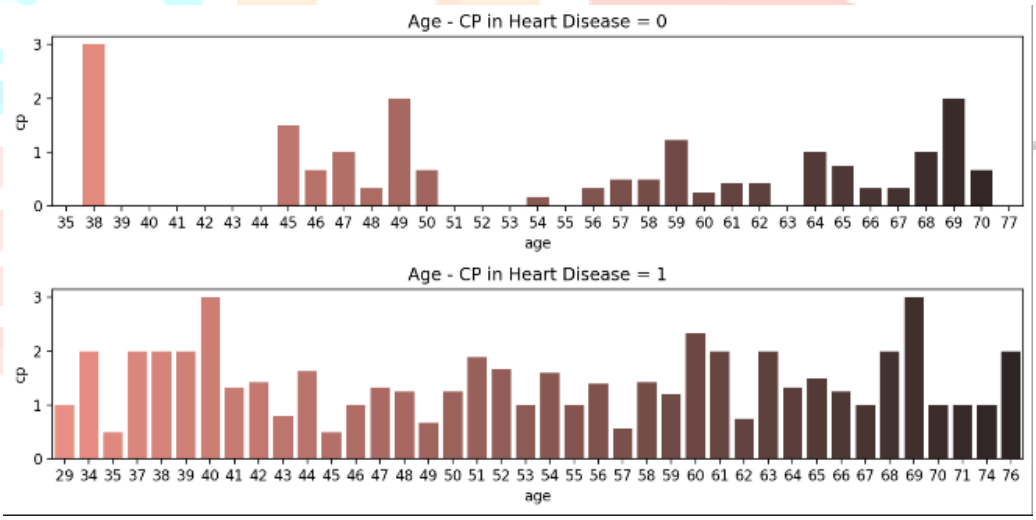

Figure 2. Age vs. Chest Pain (CP) in Heart Disease Patients

According to **Figure 3,** It shows the relationship between age and resting ECG (RestECG) values in heart disease patients. The top graph represents individuals without heart disease, while the bottom graph represents those with heart disease. Different age groups have varying RestECG values, with some ages showing higher values than others. This analysis helps in understanding the impact of age on RestECG and its correlation with heart disease

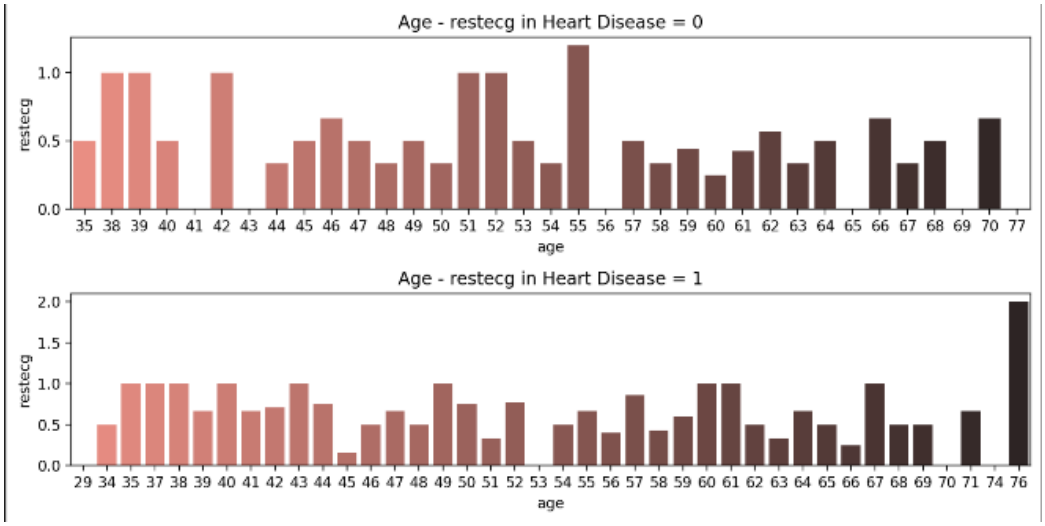

Figure 3. Age vs. Resting ECG (RestECG) in Heart Disease Patients

III. PROPOSED METHODOLOGY

1. Data Collection and Integration

The heart disease prediction system starts by collecting data from different sources like hospital records, medical reports, and wearable devices. This data includes patient details, medical history, test results, and lifestyle habits. Once collected, the data is checked for errors, organized properly, and stored securely. This process ensures that the data is correct and can be used for making predictions.

2. Data Preprocessing

Before using the data, it needs to be cleaned and prepared. If any information is missing, special methods are used to fill in the gaps. The values in the data are adjusted so that all information is in the same format. Some data, like gender and disease history, is converted into numbers to help the machine learning model understand it better. Errors and incorrect data points are also removed to improve accuracy.

3. Feature Engineering

To make better predictions, only the most important data points are selected. This includes patient age, cholesterol levels, blood pressure, and other health factors. New features are also created by combining some values, like the ratio of LDL to HDL cholesterol. Unnecessary data is removed to make the system faster and more efficient.

4. Model Development

The system uses machine learning models to predict heart disease. It includes three models: K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), and Decision Tree (DT). The KNN model finds similar cases in past data to make predictions. The SVC model identifies patterns in the data to separate healthy and at-risk patients. The Decision Tree model makes step-by-step decisions based on patient details. These models work together to improve accuracy.

4.(a) System Architecture

The system architecture, as shown in **Figure 4**, illustrates the complete workflow from data collection to prediction.

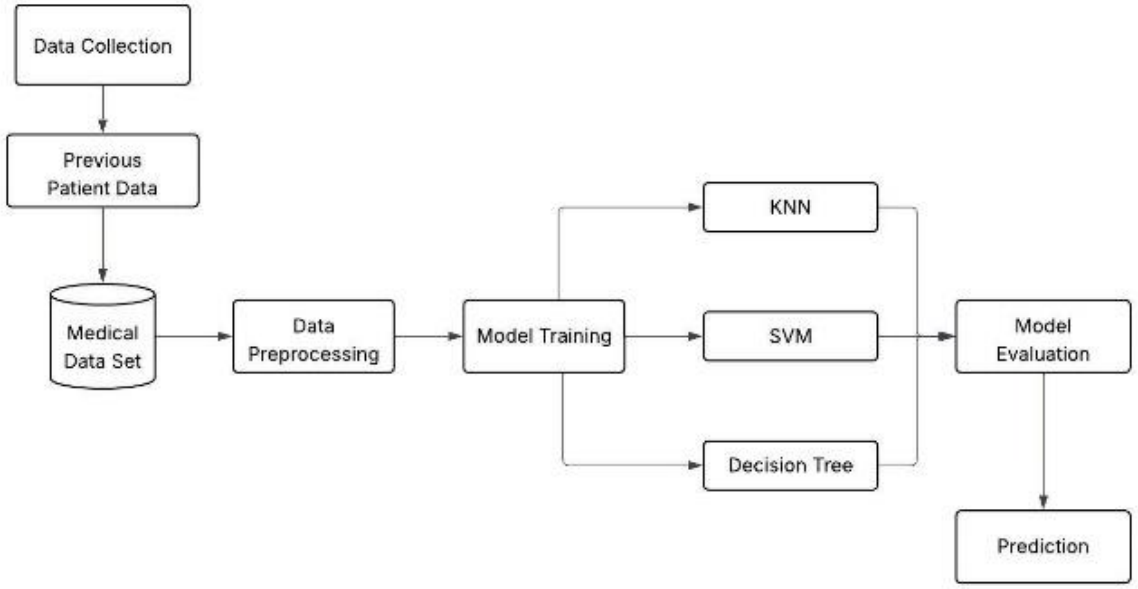

Figure [4], System Architecture

The proposed system is designed to predict medical outcomes using machine learning models. As illustrated in **Figure [4]**, the system follows a structured, multi-stage approach to ensure efficient and accurate predictions. The process begins with **Data Collection**, where patient health records, medical histories, and diagnostic reports are gathered from various sources such as **electronic health records (EHRs)** and **clinical databases**. These records are stored in a **Medical Data Set**, which serves as the foundation for analysis.

Next, the system performs **Data Preprocessing**, which involves handling missing values, normalizing data, encoding categorical variables, and detecting outliers. This step ensures that the dataset is clean, standardized, and suitable for machine learning models.
Following preprocessing, the data is used in the **Model Training** phase, where three machine learning algorithms—**K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Tree (DT)**—are trained on historical patient data. These models learn patterns and relationships within the dataset to identify potential risk factors for heart disease.

Once trained, the models undergo **Model Evaluation**, where their performance is assessed using key metrics such as **accuracy, precision, recall, F1-score, and ROC curve analysis**. The best-performing model is selected based on these evaluations to ensure reliable predictions.

Finally, in the **Prediction** stage, the trained and validated model is deployed to assess heart disease risk for new patients. The system provides classification results that assist healthcare professionals in making informed medical decisions.

This **system architecture** ensures a streamlined and effective workflow, integrating **data preprocessing, multiple machine learning models, and rigorous evaluation techniques** to enhance predictive accuracy and reliability in medical decision-making.

5. Model Evaluation

The system is tested to check how well it predicts heart disease. Accuracy is measured by checking how many predictions are correct. Precision and recall help to balance false positive and false negative results. The F1-score combines precision and recall into a single value. The ROC curve is used to check how well the system differentiates between healthy and at-risk patients. The model is also tested with new data to ensure reliability.

6. System Deployment and Integration

The final system is designed to be used by doctors and hospitals. It connects with hospital records so that doctors can access patient data easily. A user-friendly interface is created where doctors can enter patient details and get predictions. The system is updated regularly with new patient data to improve its accuracy over time.

7. Challenges and Future Enhancements

There are some challenges in developing this system, such as handling unbalanced data and improving model performance. In the future, deep learning techniques like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) can be added for better accuracy. The system can also include explainable AI features so that doctors can understand why the model made a particular prediction. Ensuring fairness in predictions for all patients is another important future improvement.

IV. RESULT AND DISCUSSION

In this study, a machine learning model was developed to predict the presence of heart disease based on various clinical parameters. The model was tested using a sample user input, as shown in **Figure 5**. The input included important features such as age, sex, chest pain type, resting blood pressure, cholesterol level, fasting blood sugar, resting electrocardiographic results, maximum heart rate, exercise-induced angina, ST depression, slope of peak exercise ST segment, number of major vessels, and thallium stress test results.

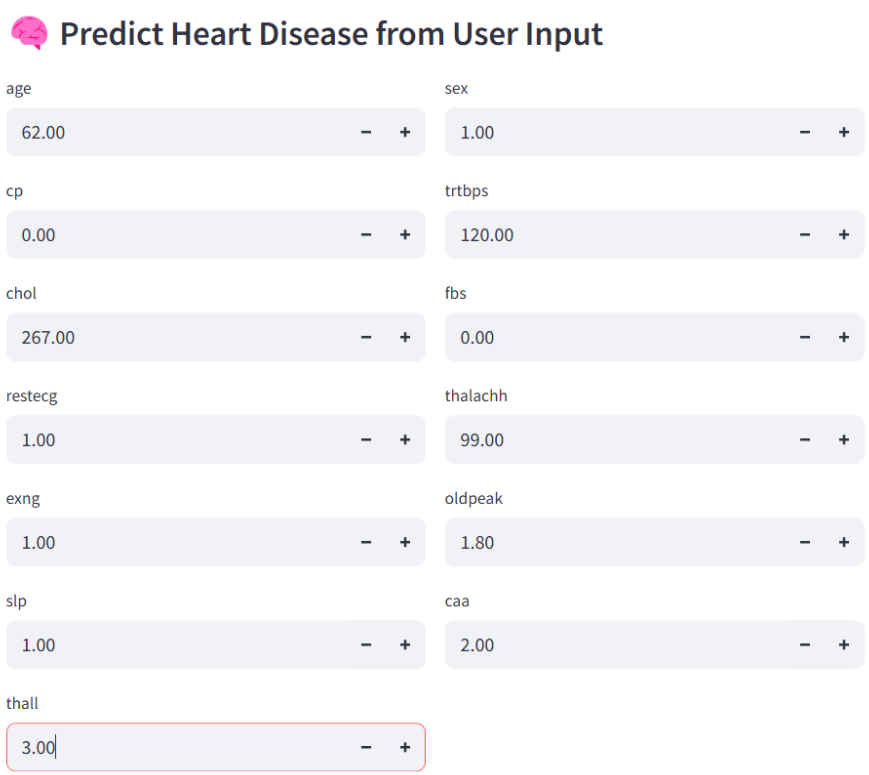

Figure 5: User Input Parameters for Heart Disease Prediction

Figure 5 displays the values entered by the user. The user was a **62-year-old male**, with a **cholesterol level of 267 mg/dL**, **resting blood pressure of 120 mm Hg**, and **maximum heart rate achieved of 99 bpm**. Additional details included **exercise-induced angina** (present) and an **abnormal thallium stress test result** (value = 3). Despite some indicators that may suggest risk factors for heart disease, the model processed all input features collectively before making a decision.

After processing the input, the model's prediction output is shown in **Figure 6**. The model confidently predicted that the individual **does not have heart disease**, with a prediction probability close to **100%** for the "No Disease" class and **0%** for the "Disease" class.

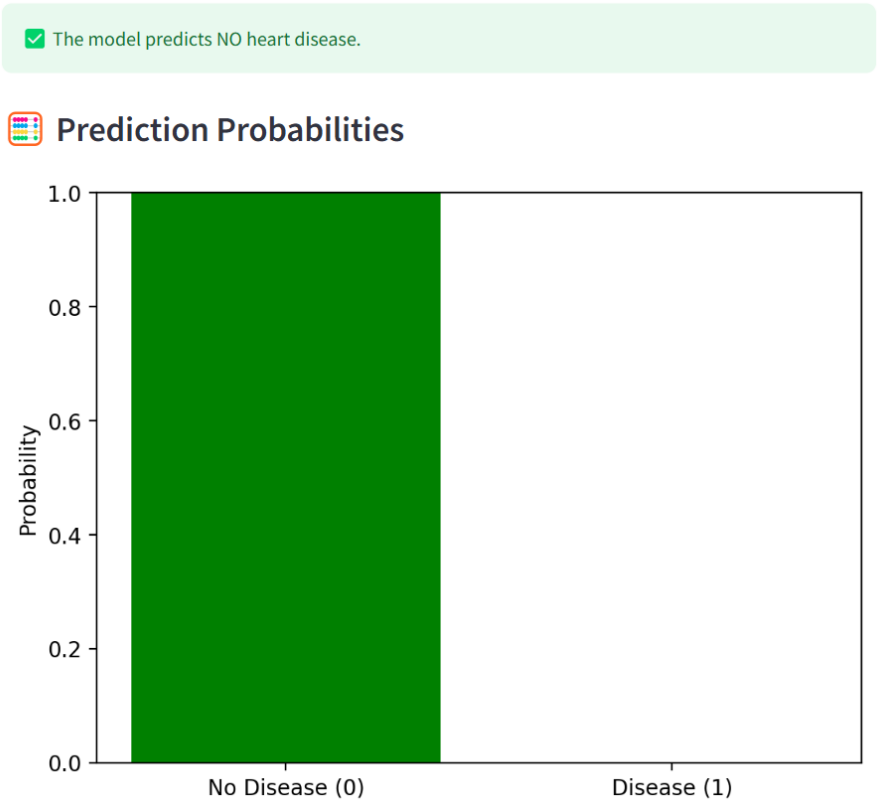

Figure 6: Model Output Showing Prediction Probability

Figure 6 presents the probability distribution, where the bar graph illustrates a high certainty in the model's prediction.
This high confidence shows the effectiveness of the machine learning model in distinguishing between healthy and potentially at-risk individuals based on multi-dimensional clinical data.

The results demonstrate that although some individual parameters like cholesterol and thallium test results were abnormal, the overall health profile was considered not critical by the model. This reflects the strength of machine learning approaches, which evaluate combinations of factors rather than isolating a single parameter for decision-making. However, it is important to note that machine learning models serve as supportive tools and should not replace professional medical diagnosis. Further improvements can be made by incorporating additional health factors such as family medical history, lifestyle habits (like smoking and alcohol consumption), and history of diabetes to enhance the model's predictive performance.

V. ACKNOWLEDGMENT

The Authors gratefully acknowledge the guidance and support provided by P. HEMA, whose expertise and encouragement were instrumental throughout the course of this project. His valuable insights contributed significantly to the development and completion of this research work.
The authors also thank the department of information technology, anand institute of higher technology, for providing the facilities and resources necessary to carry out this study.

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