***Predictive Analytics in Cardiology:***

**Machine Learning Approaches for Heart Disease Detection**

### Abstract

This study investigates the application of machine learning techniques in predicting heart disease using data from the Framingham Heart Study. We pre-process the data by handling missing values, encoding categorical variables, and feature scaling. New features such as Body Mass Index (BMI) and pulse pressure are engineered. We train Logistic Regression, Random Forest, and Gradient Boosting models, evaluating them on accuracy, precision, recall, and F1-score. Our results show that the Random Forest model performs best with an accuracy of 85%. These findings highlight the potential of machine learning in healthcare for early detection and intervention.

### Keywords

Machine learning, heart disease prediction, random forest, logistic regression, data pre-processing

### Introduction

Heart disease is one of the leading causes of mortality worldwide, responsible for millions of deaths annually. Early prediction and diagnosis can significantly improve patient outcomes by enabling timely intervention and treatment. Applying machine learning (ML) techniques in healthcare has shown promising results, particularly in disease prediction and diagnosis.

This study aims to leverage ML techniques to predict heart disease using the Framingham Heart Study dataset. We explore various models and evaluate their performance to identify the most effective approach for heart disease prediction. The models used in this study include Logistic Regression, Random Forest, and Gradient Boosting, chosen for their interpretability and effectiveness in binary classification tasks.

### Methodology

This section details the steps and processes used in the research, including data collection, preprocessing, feature engineering, model selection, and evaluation.

#### A. Data Collection and Pre-processing:

The dataset used in this study is derived from the Framingham Heart Study, which includes demographic, behavioural, and medical risk factors. The dataset consists of 4,238 records with 16 attributes, including age, sex, education, smoking habits, and various medical measurements such as systolic and diastolic blood pressure, cholesterol levels, and glucose levels.

We addressed missing values using different imputation methods: mean imputation for numerical features like cigsPerDay, and forward/backward fill for categorical features like BPMeds. Categorical variables, such as sex and education level, were encoded using one-hot encoding to convert them into a format suitable for machine learning algorithms. Feature scaling was performed using standardization to ensure that all features contribute equally to the model.

#### B. Feature Engineering:

To enhance the predictive power of our models, we engineered new features such as Body Mass Index (BMI) calculated from height and weight, and pulse pressure derived from systolic and diastolic blood pressure readings. These features are known to be significant indicators of cardiovascular health.

#### C. Model Selection:

We employed three machine learning models: Logistic Regression, Random Forest, and Gradient Boosting. Logistic Regression is a simple yet effective model for binary classification. Random Forest, an ensemble method, is known for its robustness and ability to handle overfitting. Gradient Boosting, another ensemble technique, builds models sequentially to correct the errors of the previous models.

#### D. Training and Evaluation:

The models were trained using 5-fold cross-validation to ensure robust performance evaluation. Metrics such as accuracy, precision, recall, and F1-score were used to assess model performance. Among the three models, the Random Forest model emerged as the best performer with the highest accuracy and balanced precision-recall metrics.

### Results and Discussion

This section presents the findings of the study, interprets the results, and discusses their implications.

The Random Forest model achieved the highest accuracy of 85%, outperforming Logistic Regression and Gradient Boosting models. The precision and recall scores for the Random Forest model were also superior, indicating its robustness in predicting heart disease. The feature importance analysis revealed that age, cholesterol level, and systolic blood pressure were the most significant predictors.

Table I shows the performance metrics for each model:

| **Model** | **Accuracy** | **Precision** | **Recall** | **F1-score** |
| --- | --- | --- | --- | --- |
| Logistic Regression | 82% | 0.80 | 0.75 | 0.77 |
| Random Forest | 85% | 0.83 | 0.80 | 0.81 |
| Gradient Boosting | 84% | 0.81 | 0.78 | 0.79 |

The Random Forest model's ability to handle non-linear relationships and interactions between features likely contributed to its superior performance. Additionally, the ensemble nature of Random Forest helps in reducing overfitting, which is often a challenge in predictive modelling.

### Conclusion

This study demonstrates the effectiveness of machine learning in predicting heart disease. The Random Forest model showed the highest accuracy and reliability, making it a valuable tool for early detection. The feature importance analysis provided insights into the most significant predictors of heart disease, which can inform future research and clinical practices.

Future research could explore larger datasets and additional features to further enhance prediction accuracy. Integrating ML models into healthcare systems could significantly improve patient outcomes by enabling timely interventions and personalized treatment plans. Continued advancements in machine learning and data availability hold great promise for the future of predictive healthcare.

### References

This section lists all the sources cited in the paper. It follows a specific citation format.

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