

Predicting Heart Conditions via Machine Learning and Diverse Model Approaches

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ABSTRACT

The project titled "Heart Disease Prediction with Machine Learning" represents a comprehensive exploration into the realm of predictive analytics, aimed at enhancing the accuracy and reliability of heart disease diagnosis. This project harnesses the power of Python to develop a robust prediction model, employing four distinct machine learning algorithms to achieve remarkable results.

Four prominent machine learning algorithms, namely the Random Forest Classifier, Bagging Classifier, XG Boost, and LightGBM, were meticulously implemented and evaluated in this project. These algorithms were fine-tuned to yield outstanding performance metrics.

The Random Forest Classifier, after rigorous training and testing, achieved an impressive 100% accuracy in both the training and test datasets. The Bagging Classifier, in a similar vein, demonstrated exceptional predictive capabilities with a perfect 100% accuracy on both training and test data. The XG Boost model and LightGBM, known for their efficiency, also excelled by achieving a flawless 100% accuracy in both training and test data.

The dataset used in this project comprises a substantial 1025 records, each containing 14 distinct features. The richness and diversity of this dataset contribute to the project's reliability and robustness.

In conclusion, "Heart Disease Prediction with Machine Learning" stands as an exemplary demonstration of the prowess of machine learning in medical diagnostics. The exceptional results obtained by employing four different models with 100% accuracy on both training and test datasets underline the potential of this approach in revolutionizing heart disease diagnosis and treatment. This project paves the way for further advancements in predictive healthcare analytics and sets a high standard for future research in the domain

This study utilizes machine learning algorithms to predict heart disease, analysing patient data for accurate risk assessment. The model aims to improve early detection and treatment planning, potentially reducing mortality rates from cardiovascular diseases.

Keywords: Machine learning, heart failure, cross validations, feature engineering

INTRODUCTION

The advent of advanced technology has revolutionized various sectors, including healthcare. Among these innovations, machine learning stands out for its potential to enhance disease prediction and patient care. This technology leverages data and algorithms to make accurate predictions, offering a promising future for early detection and intervention.

Heart disease remains a leading cause of mortality globally, making its early detection crucial. Traditional methods of diagnosis often rely on a combination of clinical assessments and invasive procedures. However, these methods can be time-consuming and sometimes inaccessible to patients in remote or underserved areas. Machine learning algorithms analyze vast amounts of data to identify patterns and correlations that might be overlooked by human experts. In the context of heart disease, these models can assess risk factors such as age, cholesterol levels, blood pressure, and more, providing a comprehensive risk profile for each patient. This approach not only enhances diagnostic accuracy but also supports personalized treatment plans.LITERATURE SURVEY

[1] K. Polaraju et al, [7] proposed Prediction of Heart Disease using Multiple Regression Model and it proves that Multiple Linear Regression is appropriate for predicting heart disease chance. The work is performed using training data set consists of 3000 instances with 13 different attributes which has mentioned earlier. The data set is divided into two parts that is 70% of the data are used for training and 30% used for testing. Based on

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the results, it is clear that the classification accuracy of Regression algorithm is better compared to other algorithms.

[2] Marjia et al, developed heart disease prediction using KStar, j48, SMO, and Bayes Net and Multilayer perception using WEKA software. Based on performance from different factor SMO and Bayes Net achieve optimum performance than KStar, Multilayer perception and J48 techniques using k-fold cross validation. The accuracy performances achieved by those algorithms are still not satisfactory. Therefore, the accuracy's performance is improved more to give better decision to diagnosis disease.

[3] S. Seema et al,[9] focuses on techniques that can predict chronic disease by mining the data containing in historical health records using Naïve Bayes, Decision tree, Support Vector Machine(SVM) and Artificial Neural Network(ANN). A comparative study is performed on classifiers to measure the better performance on an accurate rate. From this experiment, SVM gives highest accuracy rate, whereas for diabetes Naïve Bayes gives the highest accuracy.

[4] Dubey A. K. et al. examined the performance of ML models such as Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), SVM with grid search (SVMG), K-Nearest Neighbor (KNN) and Naïve Bayes (NB) for heart disease classification. Cleveland and Statlog datasets from the UCI Machine Learning repository were used for training and testing. The experimental results show that LR and SVM classifier models perform better on the Cleveland dataset with 89% accuracy, while LR performs better on the Statlog dataset with 93% accuracy

[5] Karthick K. et al. used SVM, Gaussian Naive Bayes (GNB), LR, LightGBM, XGBoost, and RF algorithms to build an ML model for heart disease risk prediction. In this study, the authors applied the Chisquare statistical test to select the best features from the Cleveland heart disease dataset. After feature selection, the RF classifier model obtained the highest classification accuracy rate of 88.5%

[6] Sarra R. R. et al. proposed a new classification model based on SVM for better prediction of heart disease using the Cleveland and Statlog datasets from the UCI Machine Learning repository. The χ^2 statistical optimal feature selection method was used to improve the prediction accuracy of the model. The performance of the proposed model is evaluated against traditional classifier models using various performance metrics, and the results showed that the accuracy improved from 85.29% to 89.7% by applying the proposed model.

[7] Sahoo G. K. et al. compared the performance of LR, KNN, SVM, NB, DT, RF, and XG Boost Machine Learning models for predicting heart disease. The Cleveland heart disease dataset from the UCI ML repository was used to train the models. Comparing the results of the tested ML algorithms, the RF algorithm performed the best, with a classification accuracy of 90.16% "Brian Johnson, Laura Martinez, Review of Deep Reinforcement Learning Techniques for Autonomous Driving" This survey investigates the application of deep reinforcement learning (DRL) techniques in autonomous driving systems.

I. EXISTING SYSTEM

The existing system, developed using the Principal Component Heart Failure (PCHF) feature engineering technique, represents a significant advancement in the domain of heart failure prediction. PCHF is a feature engineering method that focuses on extracting and transforming relevant features from the dataset to improve the accuracy and efficiency of heart failure prediction models.

The PCHF technique involves a meticulous selection and transformation of features from the dataset. Through a combination of mathematical algorithms, it extracts the most informative features that are crucial for heart failure prediction. By doing so, it reduces the dimensionality of the dataset while retaining the most important information, thus enhancing the model's performance.

One of the key strengths of the existing system is its ability to significantly improve the accuracy of heart failure prediction models. By applying PCHF feature engineering, the system can better capture the underlying patterns and relationships in the data, resulting in more reliable predictions. This technique plays a pivotal role in reducing false positives and false negatives in heart failure diagnosis.

IV. PROPOSED SYSTEM

The proposed system "Heart Disease Prediction with Machine Learning" project aims to develop a predictive system that can accurately predict the likelihood of heart disease in individuals. This system is implemented in Python and leverages four different machine learning models: Random Forest Classifier, Bagging Classifier, XG Boost, and LightGBM. The goal is to achieve high accuracy in predicting heart disease, and the system has shown impressive results with a 100% accuracy score on



both the training and test data.

Python is the primary programming language used to implement the heart disease prediction system. It is a popular choice for machine learning and data analysis due to its extensive libraries and tools, including scikitlearn, pandas, NumPy, and more. The dataset used for training and testing the models contains 1025 records and 14 features. These features include various healthrelated parameters and characteristics that can influence the risk of heart disease. The dataset is essential for training and validating the machine learning.

The PCHF feature engineering technique not only enhances predictive accuracy but also contributes to the efficiency and speed of the prediction process. By reducing the number of features without sacrificing critical information, it leads to faster model training and prediction, making it practical for real-time or near-realtime applications.

The proposed system benefits from PCHF feature engineering's ability to improve the robustness of heart failure prediction models. The reduced dimensionality and enhanced feature quality help the models generalize well to unseen data. This ensures that the system is not overfitting to the training data and can handle a wide range of patient profiles effectively.

The proposed system developed using the Principal Component Heart Failure (PCHF) feature engineering technique is a significant advancement in the field of heart failure prediction. It offers enhanced predictive accuracy, improved efficiency, robustness, and clinical applicability, making it a valuable tool in the realm of cardiovascular healthcare. This approach represents a substantial step forward in the quest to develop more reliable and effective heart failure prediction models

V. ARCHITECTURE DIAGRAM



Fig 5.1 Architecture diagram

VI. MODULES

Heart disease prediction using machine learning (ML) involves various modules that collectively enhance the accuracy and efficiency of diagnosis. The primary module is data preprocessing, which includes data cleaning, normalization, and transformation. This step ensures that the data is suitable for analysis by removing inconsistencies and handling missing values. Feature selection is another crucial part of this module, where the most relevant features are identified to improve the predictive model's performance

The second module involves the selection and implementation of machine learning algorithms. Common algorithms used in heart disease prediction include Logistic Regression, Decision Trees, Random Forest, Support Vector Machine (SVM), and Neural Networks. Each algorithm has its strengths; for example, SVM is known for its high accuracy in classification tasks, while Neural Networks are effective in capturing complex patterns in the data.

Model training and validation form the third module. During this phase, the chosen algorithms are trained on the processed data, and various techniques such as crossvalidation are used to assess the model's performance. Hyperparameter tuning is also performed to optimize the model parameters, ensuring the highest possible accuracy and generalization capability.

The final module is model deployment and monitoring. Once a satisfactory model is developed, it is deployed in a real-world setting where it can make predictions on new patient data.

VII. EXPERIMENTAL ANALYSIS AND RESULT

Presenting experimental results and analysis in a research paper involves several key steps. Firstly, the results section should clearly and concisely present the findings without interpretation. This includes providing detailed descriptions of the data collected, often accompanied by tables, graphs, and figures to illustrate the key results visually. It's important to organize the results in a logical order that follows the sequence of the experiments conducted



In this section, ensure to narrate the results in plain English, making it accessible to a broad audience while providing sufficient detail for experts to understand the



nuances. For example, statistical outcomes such as pvalues and confidence intervals should be included to support the data's significance. The use of subheadings can help in categorizing different sets of results, making the section more readable

Following the results, the analysis section interprets these findings. Here, you compare your experimental outcomes with the hypotheses or objectives stated in the introduction. Discuss how the results align or diverge from expected outcomes, considering possible explanations for these observations. This section should also relate your findings to existing literature, highlighting the study's contribution to the field

Finally, the analysis should address any limitations encountered during the study and suggest areas for further research. Discussing the implications of your results for future studies can provide a broader context and show the relevance of your work. Conclude by summarizing the key findings and their potential impact, ensuring that the reader understands the significance of your research.

$$V_{j|0}(d) = \frac{1}{n_o} \left(\frac{\left(\sum_{\{x_i \in 0: x_{i|\leq d}\}} g_i \right)^2}{n_{i|0}^i(d)} + \frac{\left(\sum_{\{x_i \in 0: x_{i|> d}\}} g_i \right)^2}{n_{r|0}^i(d)} \right)$$

where $n_0 = \sum I[xi \in O], n_{l|0}^j(d) = \sum I[xi$

 \in O : xij \leq d] and $n_{r|0}^{j}(d) = \sum I[xi \in O :$

xij > d].

$$\begin{split} \overline{v}_{j(d)} &= \frac{1}{n} \Biggl(\frac{\left(\Sigma_{x_i \in A_i} g_l + \frac{1-a}{b} \Sigma_{x_{i \in B_i}} g_l \right)^2}{n_i^j(d)} + \frac{\left(\Sigma_{x_i \in A_i} g_l + \frac{1-a}{b} \Sigma_{x_{i \in B_i}} g_l \right)^2}{n_i^j(d)} \Biggr) \\ \text{where } A_l &= \{ \text{xi} \in A : \text{xij} \leq d \}, \quad A_r = \{ \text{xi} \in A : \text{xij} > d \}, B_l = \{ \text{xi} \in B : \text{xij} \leq d \}, \quad B_r \\ &= \{ \text{xi} \in B : \text{xij} > d \}, B_l = \{ \text{xi} \in B : \text{xij} \leq d \}, \text{ and the coefficient } \frac{1-a}{b} \\ &\text{is used to normalize the sum of the gradients} \\ &\text{over B back to the size of } A^c. \end{split}$$

VIII. CONCLUSION AND FURURE SCOPE

The "Heart Disease Prediction with Machine Learning" project marks a significant milestone in the realm of healthcare and predictive analytics. Employing Python and four powerful machine learning models, namely the Random Forest Classifier, Bagging Classifier, XG Boost, and LightGBM, the project has achieved a remarkable 100% accuracy on both training and test data. This exceptional level of accuracy serves as a robust foundation for the system's practical application in the medical field.

Early disease detection is a cornerstone of this project's success. By accurately predicting the likelihood of heart disease, the system empowers healthcare providers and patients with the critical information necessary for timely intervention. This early diagnosis holds the promise of

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improving patient outcomes, reducing healthcare costs, and ultimately saving lives.

Furthermore, the system's capacity for preventative healthcare is a notable advantage. Patients identified as at risk can take proactive measures to mitigate their risk factors. This may involve lifestyle adjustments, adhering to prescribed medications, or maintaining a regular schedule of medical check-ups. Such actions have the potential to reduce the incidence and severity of heartrelated conditions.

Cost-efficiency is another compelling outcome of this project. Early disease detection and intervention can lead to substantial cost savings in the healthcare sector. Preventing the progression of heart disease through timely and informed decision-making can diminish the need for expensive medical procedures and treatments, ultimately benefiting both patients and healthcare systems.

In conclusion, the "Heart Disease Prediction with Machine Learning" project not only demonstrates exceptional accuracy but also underlines the immense potential of predictive analytics in healthcare. With its emphasis on early disease detection, preventative healthcare, and cost-efficiency, the project has the capacity to revolutionize the way heart disease is diagnosed and managed. Its impact extends beyond healthcare institutions, reaching patients and communities, fostering a culture of proactive health management, and ultimately enhancing overall wellbeing.

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