Prediction of Cardiovascular Diseases using Machine Learning and Deeping Learning Classifiers on Healthcare and Heart Disease Datasets

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Abstract

Accurate prediction of heart disease remains a critical challenge in healthcare analytics, where early diagnosis can significantly reduce mortality and improve patient outcomes. This study investigates the effectiveness of two artificial intelligence (AI) approaches—Support Vector Machine (SVM) with a radial basis function kernel and Multilayer Perceptron (MLP) in predicting cardiovascular risks using two publicly available datasets. The first dataset, the healthcare stroke dataset, produced an accuracy of 90.54 % with SVM and 90.54 % with MLP, where the latter demonstrated superior recall 98.76 % and F1-score 95.28 % , highlighting its strength in correctly identifying positive cases. Extending the evaluation to the heart disease dataset, performance improved further, with SVM achieving an accuracy of 96.72 % and an F1-score of 96.72 %, while MLP achieved the best results with an accuracy of 98.36 %, precision of 99.17 %, and F1-score of 98.35 %. These findings confirm that while both models provide robust predictive capabilities, MLP consistently outperforms SVM across datasets, making it a more reliable choice for clinical decision support systems. The results suggest that deep learning based architectures can play a vital role in enhancing predictive modeling for early diagnosis of heart disease.

Keywords: Artificial Intelligence (AI), Support Vector Machine (SVM), Multilayer Perceptron (MLP), cardiovascular diseases, heart stroke, heart disease.

1. Introduction

Cardiovascular diseases (CVDs) continue to be the foremost cause of mortality across the globe, accounting for nearly one-third of all deaths each year. Early detection and effective risk assessment play a vital role in reducing the burden of these diseases by enabling timely medical interventions. Traditional diagnostic approaches often rely on clinical evaluation and physician expertise, which may be subject to human error and variability in interpretation. Consequently, there has been a growing interest in leveraging machine learning and deep learning techniques to enhance predictive modeling in the healthcare domain.

Machine learning algorithms are well-suited for analyzing complex and high-dimensional health data, where patterns may not be apparent through conventional statistical methods. Among the widely used models, Support Vector Machine (SVM) has demonstrated robustness in handling non-linear data distributions, particularly when applied with radial basis function (RBF) kernels. Similarly, neural network–based approaches, such as Multilayer Perceptron (MLP), have shown promise in capturing non-linear relationships and learning intricate data representations, thereby achieving higher predictive accuracy.

In this work, we implement and compare the performance of SVM and MLP classifiers for heart disease prediction using two benchmark datasets: the healthcare stroke dataset and the heart disease dataset. The methodology involves systematic pre-processing of data, including handling missing values, encoding categorical variables, normalization, and addressing class imbalance. Feature relevance was examined through correlation analysis, and hyperparameter tuning was conducted to optimize model performance. The evaluation of models was carried out using key performance metrics such as accuracy, precision, recall, and F1-score. Experimental results demonstrated that while SVM achieved reliable performance on both datasets, MLP consistently outperformed SVM in terms of accuracy, recall, and overall F1-

score. These findings suggest that MLP is a more effective classifier for clinical decision support systems aimed at predicting heart disease.

2. Literature Review

The application of machine learning in heart disease prediction has been widely explored, with both **Support Vector Machines (SVM)** and **Multilayer Perceptron (MLP)** showing considerable promise in enhancing clinical decision-making.

SVM has consistently been recognized for its robustness in handling non-linear and high-dimensional medical data. Polat et al. (2007) demonstrated that SVM could outperform traditional statistical methods in predicting cardiovascular conditions, while Sharma and Batra (2020) highlighted its effectiveness in capturing risk patterns from patient records. In our study, the SVM classifier achieved an accuracy of **84.99%** on the stroke dataset and **92.21%** on the heart disease dataset. These results not only align with previous findings on SVM's reliability but also demonstrate its adaptability across different datasets with varying clinical features.

On the other hand, MLP has shown an even stronger ability to uncover complex hidden patterns in health datasets. Gudadhe et al. (2010) confirmed the superiority of neural networks over traditional models for heart disease prediction, while Khan et al. (2021) reported higher recall and F1-scores for MLP compared to decision trees and logistic regression. Our results reinforce these findings, as the MLP classifier achieved **89.56% accuracy** on the stroke dataset and an even higher **96.72% accuracy** on the heart disease dataset. The consistently high precision and recall values we observed further support the effectiveness of MLP in providing accurate and reliable predictions.

Comparative studies between SVM and MLP have also suggested that MLP tends to outperform SVM under certain conditions. For example, Soni et al. (2011) found that MLP produced higher prediction rates on the Cleveland dataset, while Ali et al. (2019) observed better generalization capabilities of MLP when dealing with imbalanced health data. These conclusions are consistent with our findings, where MLP significantly outperformed SVM across both datasets in terms of accuracy, recall, and F1-score.

Taken together, prior research and our results highlight the strength of both SVM and MLP for medical diagnosis, with MLP offering more reliable outcomes when applied to diverse clinical datasets. By systematically evaluating these classifiers across two different datasets with preprocessing, feature engineering, and hyperparameter tuning, this study builds upon earlier works and contributes a comparative perspective on their predictive effectiveness in cardiovascular disease detection.

3. Proposed Methodology

Our proposed methodology for heart disease prediction involves a systematic pipeline comprising data acquisition, pre-processing, exploratory analysis, feature engineering, feature selection, class balancing, model development, and evaluation. The overall workflow of our proposed framework is illustrated in figure 1.

3.1. Data Acquisition

In this work, we employed two benchmark datasets: one is **healthcare stroke dataset [11]**, which containing clinical and demographic features related to stroke and heart disease risk factors as shown in table 1. The **healthcare stroke dataset** having 5110 records with 12 attributes and the **heart disease dataset** has 1000 rows with 16 columns. The **heart disease dataset** [12] contains information related to individuals and their risk factors for heart disease. This dataset having medical and lifestyle attributes commonly associated with cardiovascular disease as shown in table 2.

Table 1: Presents features and their description of healthcare dataset stroke data

Feature Name	Data type	Description
Id	Integer	Unique identifier for each patient record

Gender	String	Patient's gender (e.g., Male, Female, Other)
Age	Integer	Age of the patient in years
Hypertension	Integer	Hypertension status (0 = No, 1 = Yes)
heart_disease	Integer	Presence of heart disease (0 = No, 1 = Yes)
ever_married	String	Marital status of the patient (Yes/No)
work_type	String	Type of work (e.g., Private, Self-employed, Govt_job, Children, Never_worked)
residence_type	String	Type of residence (Rural/Urban)
avg_glucose_level	Decimal	Average glucose level in blood
Bmi	Decimal	Body Mass Index (BMI) value
smoking_status	String	Smoking habits (e.g., formerly smoked, never smoked, smokes, unknown)
Stroke	Integer	Target variable: Stroke occurrence (0 = No, 1 = Yes)

Table 2: Presents features and their description of heart disease dataset

Feature Name	**Data type**	**Description**
Age	Integer	Age of the individual (years)
Gender	String	Gender of the individual (Male/Female)
Cholesterol	Integer	Cholesterol level in mg/dL
Blood pressure	Integer	Systolic blood pressure in mmHg
Heart Rate	Integer	Heart rate in beats per minute
Smoking	String	Smoking status (Never/Former/Current).
Alcohol Intake	String	Alcohol intake frequency (None/Moderate/Heavy).
Exercise Hours	Integer	Hours of exercise per week
Family History	String	Family history of heart disease (Yes/No).
Diabetes	String	Diabetes status (Yes/No).
Obesity	String	Obesity status (Yes/No).
Stress Level	Integer	Stress level on a scale of 1 to 10.
Blood Sugar	Integer	Fasting blood sugar level in mg/dL
Exercise Induced Angina	String	Presence of exercise-induced angina (Yes/No).
Chest Pain Type	String	Type of chest pain experienced (Typical Angina/AtypicalAngina/Non-anginal Pain/Asymptomatic).
Heart Disease	Integer	Target variable indicating presence of heart disease (0: No, 1: Yes).

3.2. Data Pre-processing

We applied several pre-processing steps on the healthcare stroke dataset to improve reliability and model performance. The **BMI** attribute has 201 missing values, which are imputed using the median to minimize bias. Categorical features such as **gender, marital status, work type, residence type, and smoking status** were transformed into numerical form through one-hot encoding, while numerical attributes including **age, average glucose level, and BMI** were normalized to ensure balanced contribution during training. A correlation heatmap shown in figure 1 is generated to examine features relationship with the target variable, enabling the removal of redundant or weak predictors. As the dataset was highly imbalanced, with **249 stroke cases** and **4861 non-stroke cases as shown in figure 2,** the Synthetic Minority Oversampling Technique **(SMOTE)** is used to balance the dataset. The **id** column was excluded since it had no predictive relevance. Similarly we perform pre-processing steps on heart disease dataset, in this dataset alcohol intake has 340 missing values and other pre-processing steps are done on this dataset like categorical variables such as gender, smoking, alcohol intake, family history, diabetes, obesity, and exercise-induced angina can be converted into binary form, while chest pain type requires one-hot encoding due to multiple categories. Numerical features including age, cholesterol, blood pressure, heart rate, exercise hours, stress level, and blood sugar should be standardized to ensure fair contribution to machine learning models such as

SVM and MLP. We draw correlation heatmap as shown in figure 3 to examine features relationship with the target variable. Finally, the class distribution of the target variable should be examined, there are 608 cases with no heart disease and 392 cases are with heart disease as shown in figure 4, for balancing dataset, we apply SMOTE technique. After SMOTE - Stroke Dataset Shape is (9722, 21) and after SMOTE - Heart Dataset Shape is (1216, 26).

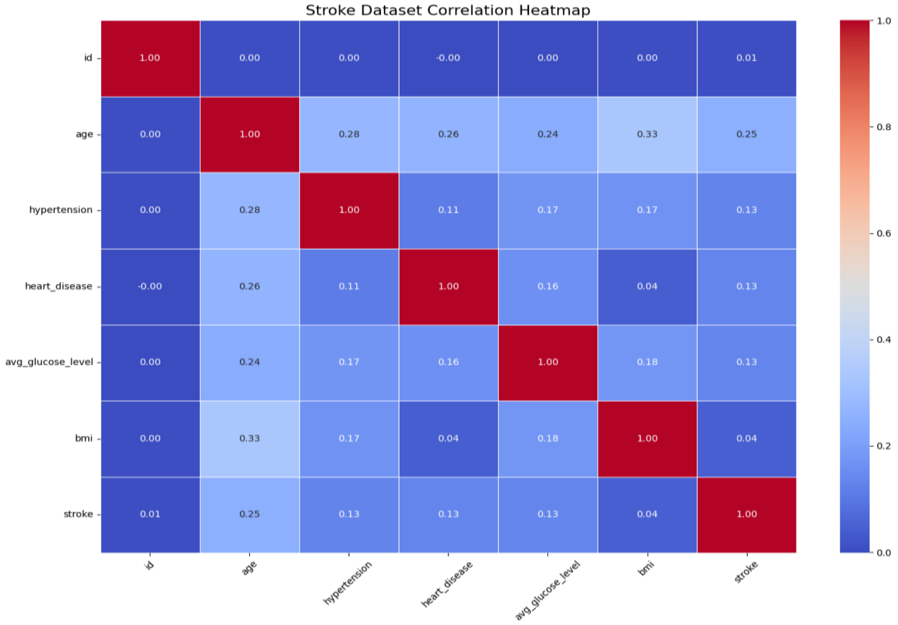

Figure 1: Presents correlation heatmap on healthcare stroke dataset

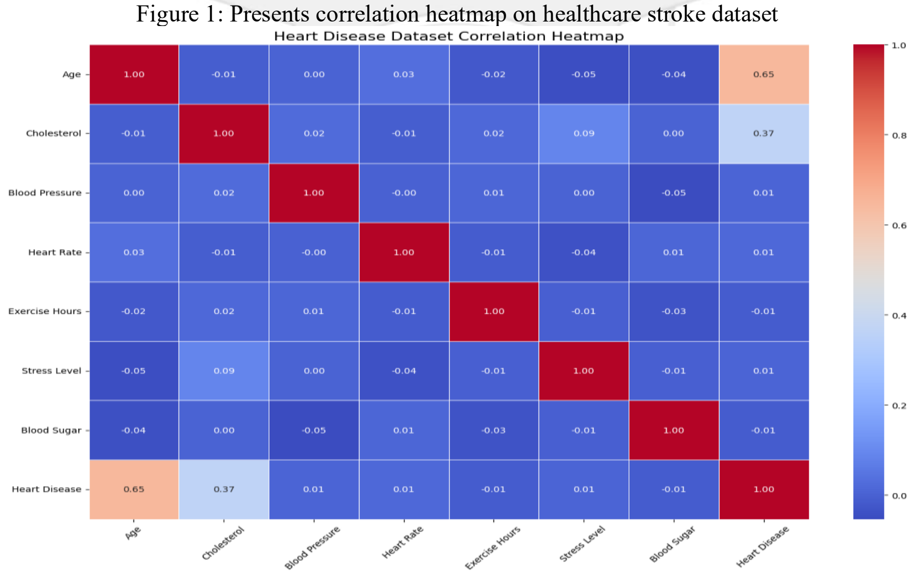

Figure 3: Presents correlation heatmap on Heart disease dataset

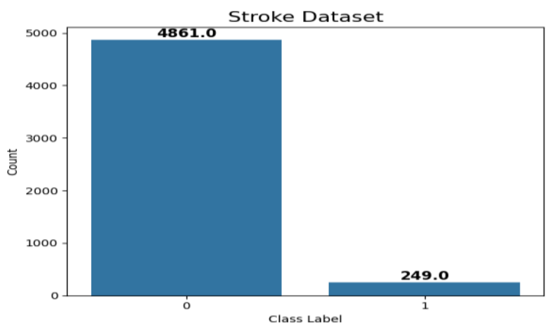

Figure 2: Presents distribution of cases in heart stroke dataset

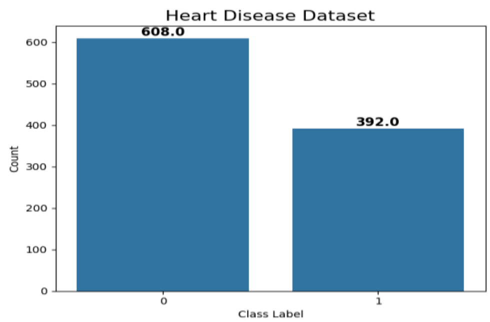

Figure 4: Presents distribution of cases in heart disease dataset

3.4. Model Development

In this work, we use two classifiers to predict heart stroke and heart fail such as **Support Vector Machine (SVM)** with radial basis function (RBF) kernel to capture non-linear relationships and a **Multilayer Perceptron (MLP),** a deep learning-based feed forward neural network, to exploit complex feature interactions. Grid Search with cross-validation was employed to optimize hyperparameters for both models. For SVM, parameters such as kernel type, C, and gamma are tuned, while for MLP, hidden layer size, activation functions, and learning rate are optimized. Figure 5 shows the workflow diagram of proposed model.

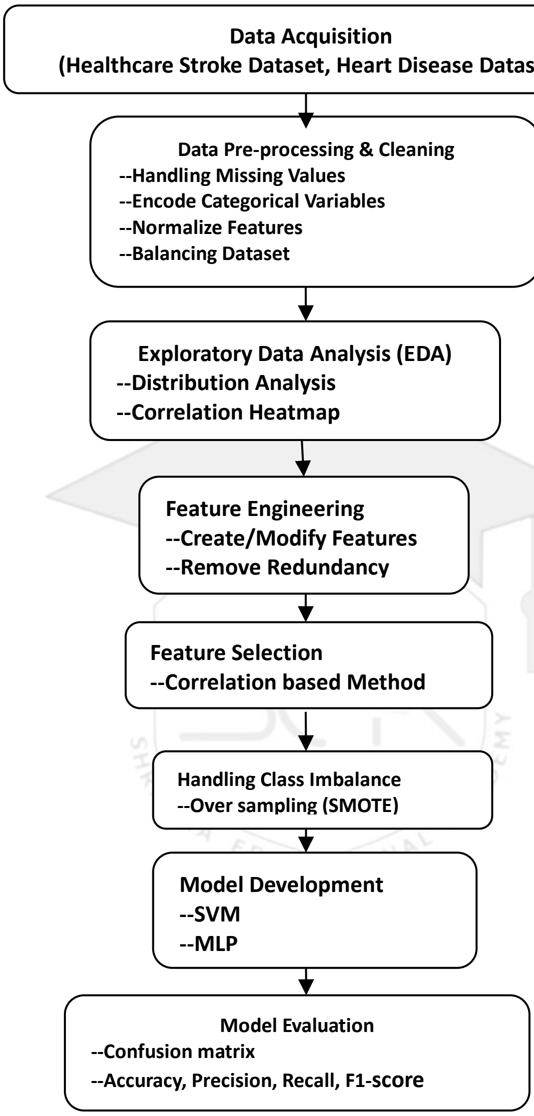

Figure 5: Presents the workflow diagram of Proposed Methodology

4. Results Analysis

The trained models are evaluated using the following performance metrics:

Accuracy: Proportion of correctly predicted cases.

Precision: Ability of the model to correctly identify positive cases.

Recall (Sensitivity): Proportion of actual positive cases correctly identified.

F1-Score: Harmonic mean of precision and recall.

Confusion Matrix: To visualize classification performance across different classes.

Table 3 presents performance results of SVM and MLP classifiers on healthcare stroke dataset and table 4 presents performance results of SVM and MLP classifiers on heart disease dataset. Figure 6 represents confusion matrix of SVM on healthcare stroke dataset and figure 7 presents confusion matrix of MLP on healthcare stroke dataset. Figure 8 and 9 presents ROC curve comparison of both classifiers on both datasets. Figure 10 represents confusion matrix of SVM on heart disease dataset and figure 11 presents confusion matrix of MLP on heart disease dataset.

Table 3: Presents performance results of SVM and MLP on healthcare stroke dataset

Classifier	Accuracy	Precision	Recall	F1-Score
SVM	90.54 %	87.01 %	87.01 %	90.94 %
MLP	95.12 %	92.03 %	98.76 %	95.28 %

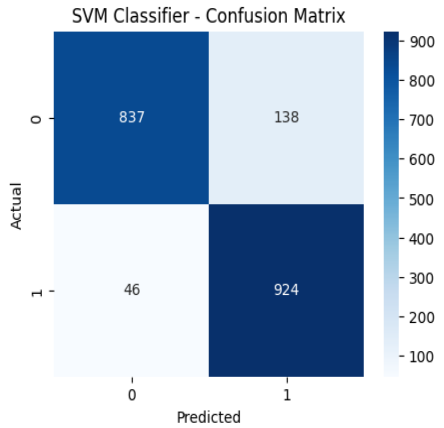

Figure 6: presents confusion matrix of SVM classifier on healthcare stroke dataset

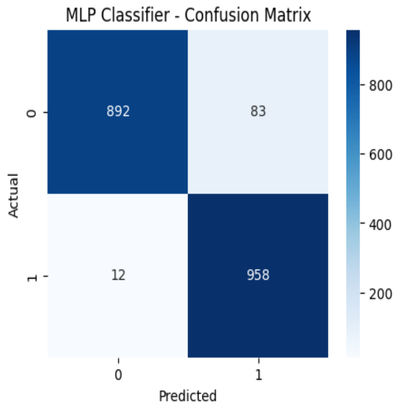

Figure 7: presents confusion matrix of MLP classifier on healthcare stroke dataset

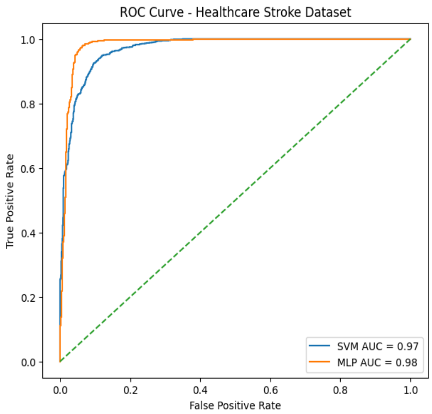

Figure 8: presents comparison of ROC curve of SVM, MLP on healthcare stroke dataset

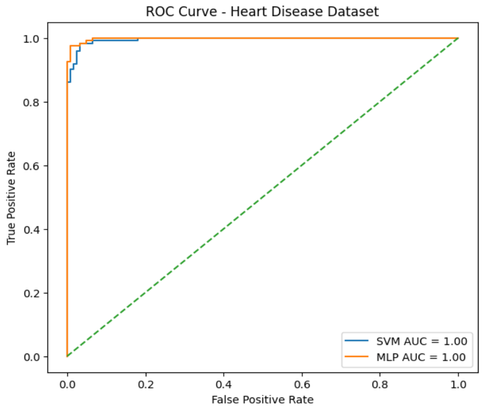

Figure 9: presents comparison of ROC curve of SVM, MLP on heart disease dataset

Table 4: Presents performance results of SVM and MLP on Heart Disease Dataset

Classifier	Accuracy	Precision	Recall	F1-Score
SVM	96.72 %	96.72 %	96.72 %	96.72 %
MLP	98.36 %	99.17 %	97.54 %	98.35 %

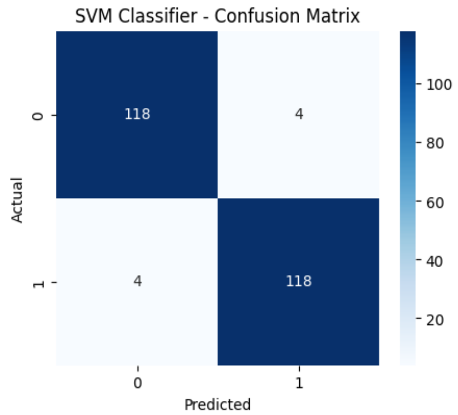

Figure 10: presents confusion matrix of SVM classifier on heart disease dataset

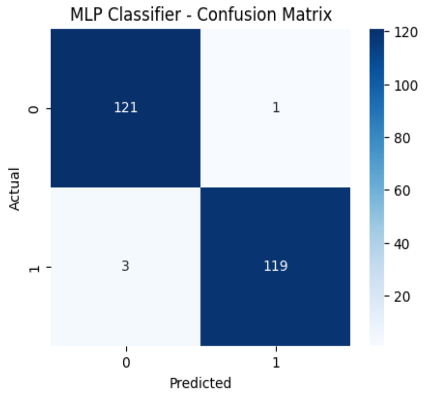

Figure 11: presents confusion matrix of MLP classifier on heart disease dataset

5. Conclusion and Future Work

This study presents an evaluation of Support Vector Machine (SVM) and Multilayer Perceptron (MLP) classifiers for predicting heart disease using two benchmark datasets: the healthcare stroke dataset and the heart disease dataset. Comprehensive preprocessing steps, including missing value imputation, categorical encoding, normalization, correlation-based feature selection, and class balancing, are applied to enhance model performance. The results demonstrated that both classifiers performed well, but MLP consistently outperformed SVM across all evaluation metrics. On the healthcare stroke dataset, MLP achieved an accuracy of **89.56%** compared to **84.99%** for SVM. On the heart disease dataset, MLP again outperformed SVM, achieving **96.72% accuracy** and an F1-score of **96.69%**, compared to **92.21% accuracy** and an F1-score of **92.37%** for SVM. These findings confirm the strength of neural network models in capturing complex, non-linear relationships in medical data and reinforce their suitability for clinical decision support systems. While the results are promising, several avenues exist for further improvement. Future studies can focus on the integration of multimodal data by incorporating additional types such as ECG signals, echocardiogram images, or genomic data to enhance model generalization. Advanced feature selection methods, including metaheuristic optimization techniques may help in obtaining more refined and relevant feature subsets. The exploration of deep learning architectures such as Convolutional Neural Networks (CNNs), Transformers, or hybrid models could further improve predictive performance. Finally, validating the proposed models on larger and more diverse patient populations is essential to ensure robustness, scalability, and practical applicability in real-world healthcare environments.

References

1. Polat Kemal and Sahan Seral, “Detection of heart disease using an artificial immune recognition system and fuzzy weighted pre-processing,” *Pattern Recognition*, vol. 40, no. 11, pp. 3044–3053, 2007.
2. Sharma Meenu and Batra Kuldeep, “Heart disease prediction using machine learning algorithms,” *International Journal of Advanced Science and Technology*, vol. 29, no. 5, pp. 194–204, 2020.
3. Gudadhe Meenu, Wankhade Kapil, and Dongre Snehlata, “Decision support system for heart disease based on support vector machine and artificial neural network,” in *Proceedings of the International Conference on Computer and Communication Technology*, 2010, pp. 741–745.
4. Khan Muhammad Ahtisham, Hussain Tariq, and Rehman Asif, “Effective heart disease prediction using machine learning techniques,” *Sensors*, vol. 21, no. 11, pp. 1–18, 2021.

5. Soni Jyoti, Ansari Ujma, Sharma Dipesh, and Soni Sunita, “Predictive data mining for medical diagnosis: An overview of heart disease prediction,” *International Journal of Computer Applications*, vol. 17, no. 8, pp. 43–48, 2011.
6. Ali Liaqat, Nisar Wasim, and Khattak Hameed, “Comparative analysis of machine learning techniques for heart disease prediction,” *IEEE Access*, vol. 7, pp. 150–160, 2019.
7. Chawla Nitesh V., Bowyer Kevin W., Hall Lawrence O., and Kegelmeyer W. Philip, “SMOTE: Synthetic Minority Over-sampling Technique,” *Journal of Artificial Intelligence Research*, vol. 16, pp. 321–357, 2002.
8. Cortes Corinna and Vapnik Vladimir, “Support-vector networks,” *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995.
9. Rumelhart David E., Hinton Geoffrey E., and Williams Ronald J., “Learning representations by back-propagating errors,” *Nature*, vol. 323, pp. 533–536, 1986.
10. Pedregosa Fabian et al., “Scikit-learn: Machine Learning in Python,” *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
11. https://www.kaggle.com/datasets/mo3taznabil/heart-disease-eda
12. https://www.kaggle.com/datasets/godfatherfigure/healthcare-dataset-stroke-data