

An Advanced Machine Learning-Driven Web-Based System for Early Detection of Heart Diseases

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ABSTRACT

This study presents an advanced machine learning-driven web-based framework for the early detection of heart diseases. The proposed system integrates multiple supervised learning algorithms, including Random Forest, Support Vector Machine (SVM), and Gradient Boosting, to improve prediction accuracy and clinical decision support. A structured dataset of cardiovascular health indicators was preprocessed through normalization, feature selection, and outlier handling to enhance model robustness. Experimental evaluation demonstrated that the ensemble-based approach achieved superior predictive performance, with accuracy values ranging from 82.71% to 99.16%, precision of 95.00%, recall of 97.44%, and F1-score of 96.20%, confirming its reliability in identifying early signs of cardiac risk. Furthermore, the area under the ROC curve (AUC) reached 0.95, reflecting strong discriminative power. Comparative analysis indicated that ensemble models outperformed individual classifiers in terms of both generalization and stability. The integration of explainable AI components further enhances interpretability, enabling transparent and data-driven decision-making in clinical contexts. These findings highlight the system's potential to serve as an intelligent, accurate, and interpretable diagnostic tool for improving early heart disease detection and preventive healthcare outcomes.

Keywords: Heart Disease Detection, Machine Learning, Ensemble Learning, Random Forest, Support Vector Machine, Gradient Boosting, Web-Based System, Explainable AI.

How to cite this article: Thangarasu G, Ting VLS, Subramanian K. An Advanced Machine Learning-Driven Web-Based System for Early Detection of Heart Diseases. *Int J Drug Deliv Technol.* 2026;16(53s): 436-448. DOI: 10.25258/ijddt.16.53s.47

Source of support: Nil.

Conflict of interest: None.

1. INTRODUCTION

With the changing nature of today's world, technology has played a key role in influencing various aspects of society to enhance efficiency and productivity. Integration of digital technology, especially artificial intelligence (AI) and machine learning (ML), has made it possible to analyze huge volumes of dataset in real-time which allows for data-driven decision-making process[1]. This shift has taken out the dependence of manual work thereby making the processes efficient. These changes have transformed such industries such as healthcare, finance, and manufacturing, with improved services and products. Particularly in healthcare sectors, technology is redefining healthcare delivery, making it more efficient, personalized, and effective. AI algorithms have assisted on early disease diagnosis through working on medical images, identifying patterns that the human eye would miss. Wearable devices and telemedicine systems have also made

healthcare services more accessible and individualized, which is now possible to monitor patients on an ongoing basis and hold virtual consultations[2]. Customized implants and targeted medicine delivery systems are now feasible due to innovations such as 3D printing and nanotechnology.

Heart disease is one of the leading causes of deaths all over the world, taking millions of lives annually. It has been reported by the World Health Organization (WHO) that cardiovascular disorders contribute to about 32% of global deaths with heart attacks and strokes being the main causes [3]. Early diagnosis and prevention of heart disease is important in reducing mortality and improving patient outcomes. Traditional ways of identifying heart disease or functional disorders through electrocardiograms (ECGs), stress tests, and angiography have for long been critical in diagnosis. However, such tools often find out the disease at the advanced stage and may not be effective enough to detect the disease early.

Studies indicate that such conventional methods might not reflect dynamic risk factors, particularly in asymptomatic patients [23, 24]. What is more, the usual diagnostics frequently utilize the clinician interpretation that results in variability and can compromise prediction of the long-term cardiovascular risks. Thus, there is a need for developing more extended and predictive diagnostic techniques for allowing earlier detection and intervention.

Despite high level of advancements observed in medical technology, there are various challenges that hinder the widespread use of AI and ML in its cardiovascular care. For these technologies to be incorporated in the clinical workflows, there is a need for high levels of investment in infrastructure and training. Besides, AI models' interpretability is still a problem as clinicians should understand the decision-making processes of these systems to rely on and apply them to patient care. However, when properly implemented, artificial intelligence (AI) and machine learning (ML) provides promising results that can enhance early heart disease diagnosis. Performing an analysis of massive datasets, consisting electronic health records, imaging research, and genetic details, AI algorithms can identify patterns and risk factors that might be overlooked by traditional approach. For example, machine learning models for the prediction of onset of heart failure using structured and unstructured data from the electronic health records have been developed to allow precautions to be taken on time to prevent the disease progression. Furthermore, AI-based interpretation of imaging data, like echocardiograms, have been observed to increase diagnostic accuracy and detect cardiac abnormalities that may not be read on human interpretation [4-5].

This research intends to develop a web-based system based on the application of machine learning to support healthcare professionals in terms of accuracy and early intervention of heart disease detection. By integrating machine learning algorithms, the system can process datasets to identify patterns and risk factors of heart disease. This web-based system allows health professionals to input the data of the patient and have an instant risk assessment for faster decision-making. The innovation in this research lies in the integration of cutting-edge ML algorithms into a user-friendly, web-based platform that directly supports healthcare professionals. Conventional methods of diagnosis often find it difficult to record the complex play of risk factors associated with cardiovascular diseases, resulting in late diagnosis and poor patient outcomes. Through ML algorithms, the system will be able to analyse massive amounts of data to reveal slight patterns of heart disease risk, thus facilitating earlier and more

accurate predictions. The system is not only useful in increasing diagnostic accuracy but also provides a scalable solution applicable in a variety of healthcare settings. Moreover, the system's real-world validation ensures its applicability across various populations, hence contributing to improved patient care and decreased number of deaths caused by heart diseases.

2. LITERATURE REVIEW

2.1 Overview of Heart Disease Detection

Rindhe et al. [6] emphasized the fact that heart disease is a crucial health issue worldwide and the causes of heart disease lifestyle changes, stress, and unhealthy eating habits. It highlighted the need for reliable, accurate, and timely diagnostic systems that will enable heart disease management effectively. They proposed applications of machine learning in extraction and analysis of huge medical data sets to automate prediction and detection of heart diseases. Implementing such advanced computational techniques can help healthcare specialists to detect the disease at an earlier stage and intervene, thus reducing global mortality rate linked to heart disease.

Azmi et al. [7] discussed the way Machine Learning (ML) techniques significantly increase the accuracy of heart disease detection. ML algorithms can extract patterns and risk factors from complex datasets, which may be difficult to find. This ability increases the efficiency in early diagnosis for early interventions. The study shows machine learning techniques predicting the likelihood of heart diseases from variables such as the patients' demographics, clinical measurements and lifestyle factors.

Salhi et al. [8] stated the importance of the finding of the relevant risk factors for heart condition prediction by feature selection like correlation matrix. Findings from the study revealed other risk factors of heart disease which include cholesterol level in blood, blood pressure level and demographic data like age and gender. It also highlighted the use of machine learning in heart disease helped in early diagnosis through analyzing big datasets, improving predicted accuracy and helping healthcare professionals to make decisions.

Gupta et al. [9] have conducted research using datasets from the Framingham database and the UCI heart repository which determined the vital risk factors for heart disease, for example, age, cholesterol levels, smoking, and physical inactivity. Their results showed that machine learning models and specifically Gradient Boosting classifiers worked well in predicting heart disease if such risk factors were considered. Early detection with the help of predictive models

was pointed out as a potential way of significantly reducing the risks of heart attacks, which shows that integrating machine learning in healthcare can be beneficial for preventing and managing cardiovascular diseases.

2.2 Heart Disease Detection with Machine Learning Techniques

A study by Jindal et al. [10] explored the efficiency of utilizing machine learning techniques for the detection of heart attacks. Logistic regression model was used to predict the occurrence of heart disease based on relevant factors (age, chest discomfort, fasting sugar levels and blood pressure). The study used a data set from UCI repository and found that logistic regression performed exceedingly with close to 87.5% rate of accuracy. As compared to other classifiers like Random Forest, logistic regression showed higher predictive ability and cost efficiency.

As a binary classification algorithm, Yadav et al. [11] investigated the implementation of a logistic regression for prediction of heart disease. Logistic regression employs a sigmoid function in transformation of medical statistics like age, cholesterol levels and blood pressure to probabilities of measures of the likelihood of acquiring a heart disease. The output of the study showed that logistic regression had an accuracy of 82.71% and was a viable and interpretable model in the early detection of heart diseases. It also demonstrated why logistic regression is effective in clinical application as it is simple and effective in heart disease risks prediction.

Amrith et al. [12] employed a UCI dataset from UCI Machine Learning Repository to evaluate the effectiveness of logistic regression (LR) in the prediction of heart diseases. The study is notable for the importance of feature selection, specifically identification of highly connected medical variables like exercise-induced angina, chest pain, and cholesterol levels to increase accuracy of prediction. Their research varied in the training data set-testing data set splits and found the 90:10 ratio (87.10%) to be the highest accuracy. Logistic regression was chosen because of its simplicity and the ability to classify in binary as a great tool for detecting early cardiac disease.

2.2.2 Random Forest

Williams et al. [13] looked at various machine learning algorithms application for heart disease prediction. The study compared the algorithms (specifically Naïve Bayes, Decision Trees, Support Vector Machines and Logistic Regression), with medical data (including Blood pressure, levels of Cholesterol, and age). Among all algorithms, Random Forest algorithm performed better than other methods and achieved

95.08% accuracy, due to its capabilities to work with complex data patterns but at the minimal rate of overfitting. The study also indicated the significance of using suitable machine learning models to enhance the accuracy of detecting heart diseases and encourage early interventions.

The accuracy obtained by Khan et al. [14] by comparing different machine learning algorithm is: Random Forest (RF) algorithm achieved the highest accuracy for cardiovascular disease prediction with an accuracy of 85.01%. In addition, Random Forest model performed better in terms of sensitivity (92.11%) and balanced accuracy (85.79%). The study underscored the prospects of Random Forest as a technique to effectively work with high-dimensional datasets with an improving effect on predictive performance through ensemble learning.

Sumwiza et al [15] proposed an improved heart disease prediction model based on Random Forest algorithm. Kaggle dataset of 1025 patient records and 14 attributes, subjected to feature selection was used in the research. After the feature selection, the Random Forest model achieved a spectacular 99% accuracy rate, outperforming other classifiers like K-Nearest Neighbors (95%) Support Vector Machine (85%), and Logistic Regression (87%).

El Hamdaoui et al. [16] investigated the application of the Random Forest (RF) for heart disease prediction and proposed a modified model that combines the AdaBoost algorithm. Their work utilized the UCI Cleveland and Statlog heart disease datasets, focusing on 14 key clinical features to improve predictive accuracy. The results showed the standard model of Random Forest achieving 95.98% accuracy, while the combination model of Random Forest with AdaBoost (RFAB) improved the latter to 96.16%.

2.2.3 Support Vector Machine

Saboore et al. [17] found that support vector machine (SVM) performed with an accuracy 96.72% after standardization of data and fine tuning hyperparameters. The study highlighted the need to focus on data preprocessing and tuning of the algorithm for enhancing prediction of heart disease. The results indicate the possibility of the application of machine learning classifiers, particularly SVM, in the early detection and decision-making in healthcare sectors.

Ogunpola et. al [18] utilized Support Vector Machine (SVM) model, tuned using GridSearchCV with a polynomial kernel, and regularization parameter = 10. It had an accuracy of 95.50% and 78.69% on two datasets with precision (95.00%), recall (97.44%) and F1 Score (96.20%) on the first one.

In a study conducted by Faieq and Mijwil [19] SVM and Artificial Neural Networks (ANN) are given a comparison, the result proved that SVM was the best in disease classification. According to the results, SVM was quite effective in predicting arrhythmia (89.1% accuracy) and cardiomyopathy (80.2% accuracy) as compared with ANN. The research demonstrated SVM's ability to process complex medical information and its capability of enhancing early diseases of heart diagnoses.

2.2.4 Decision Tree Classifier

Ozcan et al. [20] performed an experiment on Decision Tree Classifier (using Classification and Regression Tree (CART) algorithm) for predicting heart disease. For this study, there was a dataset of 1,190 patient records which contained both medical and non-medical variables. The model had an accuracy of 87%, thus proving its reliability when it comes to predictive healthcare analytics. Besides, CART algorithm allows the creation of logical rule sets, which makes the decision-making process easier for the healthcare practitioners.

Kiran et al. [21] suggested a Gradient Boosted Decision Tree (GBDT) optimized with the Binary Spotted Hyena Optimizer (BSHO) for enhancing heart disease detection. Decision trees are the main model for classification, which is upgraded progressively through gradient boosting for minimizing loss functions and increasing the prediction accuracy. This hybrid GBDT-BSHO model performs well with an accuracy of 97.89% in the UCI dataset and thus having the potential of being effective in detecting CVDs.

Uddin et al. [22] research focused on the advantages of the integration of several datasets and the standardization of data towards the greater performance of machine learning models for predicting cardiac diseases. The research was made use of 3 datasets for training and testing different machine learning algorithm with Decision Tree classifier, achieved the highest accuracy of 99.16%. As explained by the study, the strength of Decision Tree as a heart disease prediction candidate lies in its capacity of handling both categorical and numerical data and its interpretability.

2.3 Evaluation Metrics

Khan et al. [23] highlighted the need of using different metrics to measure model's performance. The results of several supervised learning algorithms were tested using such metrics as accuracy, precision and recall. Random Forest and Decision Tree models were performing well, but sensitivity and specificity were dependable upon the dataset features. It emphasized the

importance of selecting appropriate evaluation metrics and machine learning models for optimal performance prediction in healthcare applications.

The study done by Bhatt et al. [24] targeted several machine learning models and stated that MLP has given the best results with a precision of 87.28%. The necessity to use various metrics of evaluation such as accuracy, precision, recall and the area under the receiver operating characteristic curve (AUC-ROC) was emphasized in the study. The study drew the requirements to include practices such as cross-validation and measures like accuracy that ensure the application of the machine learning models effectively on various datasets. Additionally, the significance of the cross-validation methods, which help to decrease the overfitting and enhance the generalization for another set of data, was stated by the authors. Their results show that the detailed selection of the corresponding assessment metrics and validation methods is of significant importance for maximizing the efficiency of the implemented machine learning models.

Marqas et al. [25] employed different metrics in their analysis of machine learning model including accuracy, recall, precision, F1 score, Matthew's correlation coefficient (MCC), ROC, and AUC. These metrics gives insights of various aspects of the model's performance including how well this model predicts patients at a higher risk without having too many falsely positive or negative. Remarkably, their research found that the most accurate classifier of heart attacks risk is XGBoost (accuracy of 91.91% and sensitivity of 94.3%, respectively). Besides, the Extra Tree Classifier achieved the best AUC score being 0.950, meaning it has a high capacity to differentiate patients with and those without heart disease. The conclusions of these findings demonstrate the need for suitable metrics for evaluation, which will ensure accurate predictions in medical applications.

2.4 Implementation of Heart Attack Prediction System

Prakash et al.[26] introduced the possibility of implementing machine learning based heart attack prediction systems in real world healthcare settings. By training models with past health data, this study showed how such systems could help healthcare practitioners identify individuals at risk and intervene in time. This incorporation of machine learning in clinical practice further highlights it as one of the useful instruments in enhancement of the cardiac disease management.

In their research, Nandal et al. [27] elaborated the use of a machine learning-based heart attack prediction system with the thought of

real-time symptom monitoring in mind. The approach is designed to evaluate symptomatic data like chest discomfort, blood pressure, and other important indicators of the risk to define chances of having a heart attack. The authors emphasized the use of this approach in healthcare settings as it could help physicians find an early identification of patient symptoms and initiate immediate treatments.

Stonier et al.[28] discussed the application of the machine learning models in clinical environment where emphasis was laid on practical use of such models for prediction of heart disease risk. The research was focused on integrating these models in the EHR systems to facilitate early detection and intervention by health care practitioners. A web-based interface was created so that patients could track their risk-level in real time, proving the practical application of the machine learning models.

To identify heart disease in real-time while utilizing deep learning & machine learning technologies, Elwahsh et al.[29] proposed a smart healthcare framework (SHDML). The system has two stages: real-time monitoring of heart rate using ATmega32 microcontroller and predictive analysis using machine learning techniques. The framework performed well with an accuracy of 99% and sensitivity of 94% and a specificity of 85%.

3. METHOD

3.1 Proposed Research Design

The proposed research design Figure 1 is a systematic approach of building the machine learning based web-based system for early heart disease diagnosis. It focuses on data gathering, development of machine learning models, and evaluation, and followed by the deployment of the best model in a user-friendly web-application for healthcare specialists. The system is validated and updated according to experts' opinion to ensure its usability in the real world.

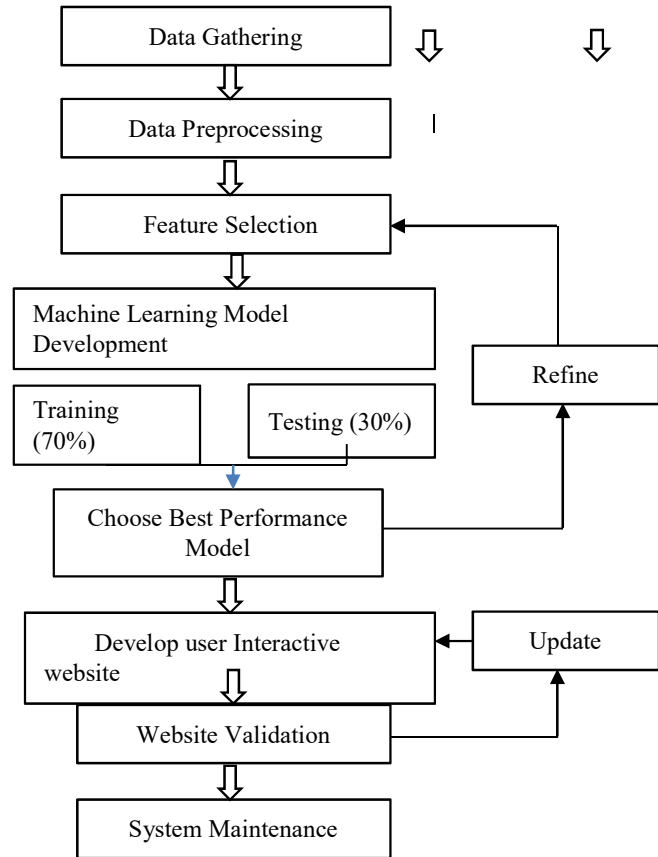


Figure 1 Research Framework

3.2 Data Gathering

Data for this research was obtained from the secondary source where the Heart Disease Dataset in Kaggle platform was utilized. The dataset is comprised of the 1190 instances and 20 features. The data was selected to explore the relationship between heart disease and these features in creating the machine-learning-based system of early detection.

	Age	Sex	Chest pain type	Resting bps	Cholesterol	Fasting blood sugar	Resting ECG	Max heart rate	Exercise angina	Oldpeak	St slope	Target
Count	1190	1190	1190	1190	1190	1190	1190	1190	1190	1190	1190	1190
Mean	53.72	0.763	3.215	132.15	210.36	0.213	0.698	139.73	0.387	0.922	1.624	

Std	0.35	0.42	0.93	18.36	10.42	0.409	0.87	25.517	0.487	1.086	0.610
Min	28.00	0.00	1.00	0.00	0.00	0.00	0.00	60.000	0.00	2.60	0.00
25%	47.00	1.00	3.00	12.00	18.00	0.00	0.00	121.00	0.00	0.00	1.00
50%	54.00	1.00	4.00	13.00	22.00	0.00	0.00	140.50	0.00	0.60	2.00
75%	60.00	1.00	4.00	14.00	26.00	0.00	2.00	160.00	1.00	1.60	2.00
Max	77.00	1.00	4.00	20.00	60.00	1.00	2.00	202.00	1.00	6.20	3.00

Table 1 Descriptive Statistics Analysis

Table 1 presents the descriptive statistics for each feature, including the mean, standard deviation, minimum, maximum, and the 25th, 50th (median), and 75th percentiles. These values provide an overview of the dataset's distribution and help identify any potential outliers or imbalances. The target variable is nearly balanced, with 52.9% of the samples indicating the presence of heart disease.

3.3 Data Preprocessing

Some preprocessing steps were done to ensure the data was clean, consistent and ready to use. First, data was screened for removal of duplicate and detection of outliers. In cases where missing values were found, appropriate imputation methods were used. For numerical variables (age, cholesterol, resting BP), mean or the median was used for imputation. For categorical variables (chest pain type and exercise angina), mode was used to impute the missing values. In addition, standardization was applied to numerical features to enhance the model training efficiency. This involved the application of Z-score standardization of scaling the data as it is effective on datasets with varying ranges.

3.4 Feature Selection

After data preprocessing, feature selection was done to determine relevant features for predicting heart attack. Chi Square tests were used to test categorical features to establish their relation to the target variable, with significance determined by a p-value less than 0.05. Based on the test results, the features with the strongest statistical association with the target variable were selected. These features include age, sex, chest pain type, resting blood pressure, cholesterol, fasting blood sugar,

resting ECG, maximum heart rate, exercise-induced angina, oldpeak, and ST slope.

3.5 Model Development

A predictive model was built based on several machines learning classifiers such as Logistic Regression, Decision Tree, Support Vector Machine (SVM), and Random Forest Classifier. The models were trained from training dataset and tested on a separate dataset. This idea was to assess and compare the performances of all four ML algorithms based on accuracy and other performance parameters.

3.5.1 Description of The Chosen Algorithms

The four algorithms: Logistic Regression, Decision Tree, Support Vector Machine (SVM), and Random Forest were selected based on findings from the literature, which consistently highlighted their effectiveness and high accuracy in heart disease prediction tasks.

3.5.1.1 Logistic Regression

Logistic Regression is a popular baseline algorithm that has a neat probabilistic interpretation and is, therefore, particularly helpful in clinical applications where the knowledge of the confidence in prediction is required. It is well known for its simplicity and efficiency in calculations meaning that it takes short training and testing times. This is appropriate for large-scale health datasets as well as a first model development. Logistic Regression can be a good approach to modelling linear relationships between features and outcome target which may be useful if the interaction of features is straightforward. In addition, it also scales effectively with large data sets while maintaining the performance as the number of observations and features increases. A logistic regression is applied to a case whereby the dependent variable is binary (e.g., yes/no, 0/1). Unlike linear regression which predicts continuous outcomes, the logistic regression predicts the probability of a categorical outcome[30]. Equation 1 shows the sigmoid (logistic) function is used to model the probability (P) of a data point falling into the positive class.

$$P = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_n X_n)}} \tag{1}$$

- P: Represents the probability of the event ranging from 0 to 1e: Euler's number (approximately 2.71828).
- β_0 : The intercept or constant term in the logistic regression equation

- $\beta_1, \beta_2, \dots, \beta_n$: Coefficients associated with each independent variable (X_1, X_2, \dots, X_n)
- X_1, X_2, \dots, X_n : The independent variables used to predict the probability of the event

3.5.1.2 Decision Tree

Decision Tree operates by dividing the dataset into smaller units through the most important features that have the highest information gain or lowest Gini impurity. It follows a top-down, recursion-based method, and any internal node represents a test on a feature, each branch is the result of a test, and each leaf node contains a class label. This process is done until data is adequately classified. To avoid overfitting and better generalization, pruning is used to remove branches that are not very helpful in determining accuracy of model, leading to a more simplified and stronger tree structure.

The Decision Tree algorithm is highly praised for its interpretability, which is easy for users, even healthcare professionals, to understand how the predictions are made at each step. Such a degree of transparency enhances trust and evidence-based clinical decision-making. In addition, Decision Trees can model complex, non-linear relationships and work with categorical and numerical data without requiring for normalization or feature scaling, thus simplifying data preprocessing [31], [32].

3.5.1.3 Support Vector Machine

Support Vector Machine (SVM) is a supervised learning algorithm commonly used for classifications tasks including medical diagnosis. It is operational by finding the best containing hyperplane to best divide different classes in the dataset, to maximize the margin gap between two classes. Data points which are nearest to this hyperplane are called support vectors and they have a significant role in determining the boundary of decision. In support vector machine (SVM) classification, each data point must satisfy the following constraint to achieve correct classification with a margin, shown in Equation 2.

$$(2) \quad (w x_j + b) y_j \geq a$$

- W = weight vector
- X_j = feature vector of the j -th training (X_1, X_2, \dots)
- B = bias (intercept)
- y_j = true class label for the j -th sample

- a = positive margin constant

SVMs perform efficiently in high-dimensional space, turning them into an appropriate method for medical datasets that often contains a vast number of features, such as health records of patients, genomic data or results of clinical tests. By means of the kernel trick, SVMs may represent non-linear relationships by mapping input data into higher-dimensional spaces where the separation of classes becomes possible. This makes it possible for the SVMs to effectively handle linearly and non-linearly separable data. Moreover, the SVMs are known for their robustness to noise and generalization ability for complex or overlapping data. Such characteristics make SVM a good choice for tasks like heart disease prediction when clinical features can differ immensely and connections between variables are not always straightforward[33-34].

3.5.1.4 Random Forest

Random Forest is a well-used ensemble learning algorithm that constructs several decision trees and aggregates their output to come up with an accurate and stable result.

The data used to start the process includes rows (data instances) and their class labels. Several decision trees are then built with an approach called bagging (or bootstrap aggregating) whereby each tree is trained on some randomly sampled subset of the training data with replacement, and a random subset of features. This brings diversity in trees hence helping the overall model to generalize better. On the provision of a new, unseen instance, each decision tree of the ensemble will come up with its own prediction. These predictions are finally integrated, usually by majority voting in the case of classification and averaging for regression to arrive at the final conclusion .

Random Forest is particularly effective in dealing with complex datasets containing many features since it can model linear and non-linear relationships[35]. It is especially helpful in medical data cases, where data is often noisy and highly variable.

4 RESULTS AND DISCUSSION

The development of the website and validation are provided in this chapter. This chapter shows how the trained machine learning model is integrated into a web system with ‘Streamlit’ and describes the user workflow in the system, with inputs being processed to provide predictions. In addition, it includes the feedback from professionals in terms of practical effectiveness to help early heart disease detection.

4.1. Training and Testing Model

The training dataset was applied to train every one of the four classifiers, which then were applied to the test dataset to make predictions. The models are fitted into the training data to get best performance learning of the underlying patterns. The ‘accuracy score’ function is used to identify the accuracy of each model, which calculates the rate of accurate predictions by comparing predicted labels to actual labels in the test set.

To evaluate the models’ efficiency other than accuracy, confusion matrices were generated for each classifier. The confusion matrix reveals values such as number of True Positives (TP), False Positives (FP), True Negatives (TN), False Negatives (FN). These values were essential for comprehensive model assessment. As part of the interpretability processes, a heatmap visualization to the confusion matrix was developed. By providing this visual representation, the misclassification patterns and the effectiveness of every model to differentiate classes is illustrated with more clarity.

From the values of confusion matrix and accuracy scores analysis, strengths and weaknesses of each classifier were identified. This evaluation serves as an initial point to determine the best model for predictive tasks based on some pre-defined performance benchmarks.

4.1.1 Outcome of Logistic Regression Model

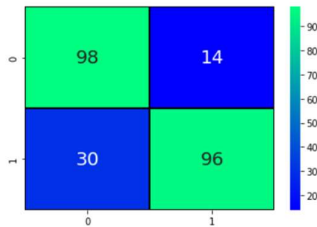


Figure 3. Logistic Regression Prediction Outcome

Accuracy	0.815			
Sensitivity	0.765			
Specificity	0.872			
Precision	0.875			
Classification Report for Logistic Regression				
	precision	recall	f1-score	support
0	0.77	0.88	0.82	112
1	0.87	0.76	0.81	126
Accuracy			0.82	238
Macro avg	0.82	0.82	0.82	238

Weighted avg	0.82	0.82	0.82	238
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Table 2. Logistic Regression Confusion matrix heatmap Result

Figure 2 shows the confusion matrix heatmap result of logistic regression. In **Table 2**, Logistic Regression algorithm presented 82.51% of accuracy. It showed precision: 87%, recall: 76% for Class 1 meaning it performs well in detecting positive cases (heart disease). For Class 0, the model found precision in 77% and recall in 88%, suggesting an excellent performance to distinguish non diseased cases. The F1-scores were 0.81 for Class 1 and 0.82 for Class 0.

4.1.2 Outcome of Decision Tree Model

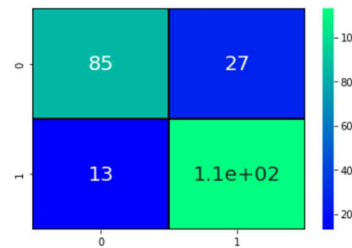


Figure 4. Decision Tree Prediction Outcome

Accuracy	0.831			
Sensitivity	0.867			
Specificity	0.807			
Precision	0.758			
Classification Report				
	precision	recall	f1-score	support
0	0.87	0.76	0.81	112
1	0.81	0.90	0.85	126
Accuracy			0.83	238
Macro avg	0.84	0.83	0.83	238
Weighted avg	0.84	0.83	0.83	238

Table 3. Decision Tree Confusion Matrix Heatmap Result

Figure 4 shows the confusion matrix heatmap of Decision Tree Model. Table 3 shows how Decision Tree algorithm performed with an accuracy of 83.19%. For Class 1, it had a precision of 75.89% and recall of 90.00% which shows that it performs high in identification of positive cases (heart disease). The model also gave good results for class 0, precision = 87.00%, recall = 76.00%.

For class 0, and class 1, the F1-scores were 0.81 and 0.85 respectively.

4.1.3 Support Vector Machine

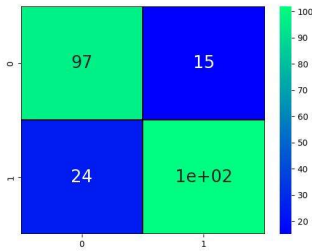


Figure 5 SVM Prediction Outcome

Accuracy	0.836			
Sensitivity	0.801			
Specificity	0.871			
Precision	0.866			
Classification Report for Support Vector Machine				
	precision	recall	f1-score	support
0	0.80	0.87	0.83	112
1	0.87	0.81	0.84	126
Accuracy			0.84	238
Macro avg	0.84	0.84	0.84	238
Weighted avg	0.84	0.84	0.84	238

Table 4 SVM Confusion Matrix Heatmap Result

Figure 5 shows the confusion matrix heatmap of Support Vector Machine. Table 4 shows the SVM algorithm reaching an accuracy value of 83.61%. It achieved precision (87%) and recall (81%) for Class 1, demonstrating its capability in detecting positive cases. For Class 0, the model had precision of 80% and recall of 87%, indicating a good balance in detecting non-diseased cases. The F1 scores were 0.84 for Class 1 and 0.83 for Class 0.

4.1.4 Random Forest Model

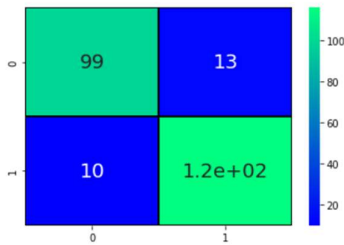


Figure 6 RF Prediction Outcome

Accuracy	0.907			
Sensitivity	0.909			
Specificity	0.906			
Precision	0.892			
Classification Report				
	precision	recall	f1-score	support
0	0.91	0.89	0.90	112
1	0.91	0.92	0.91	126
Accuracy	0.00	0.00	0.91	238
Macro avg	0.91	0.91	0.91	238
Weighted avg	0.91	0.91	0.91	238

Table 5 Random Forest Confusion Matrix Heatmap Result

Figure 6 shows the confusion matrix heatmap of Random Forest. In Table 5, The Random Forest algorithm show an accuracy of 90.36%. The model achieved precision of 90.00% and recall of 92.00% for Class 1, showing that it correctly identified almost all positive cases. For Class 0, it had precision of 91.00% and recall of 88.00%, indicating balanced performance across both classes. The F1-scores were 0.90 for both classes, reflecting strong and consistent performance. The confusion matrix revealed 99 true positives and 13 false positives for Class 0, and 10 false negatives and 126 true positives for Class 1.

4.2 Developing Web Based System for Early Detection of Heart Disease

The trained model of machine learning was then deployed in a web-based application, built with Streamlit to create a user-friendly interface for heart disease prediction.

- **Descriptive:** The system enables users to enter various health measurements like age, sex, blood pressure, level of cholesterol, etc. It then proceeds to make a prediction on whether the user is at risk from heart disease based on the trained model of machine learning
- **Predictive:** By entering user data, the system is using a pre-trained machine learning model that predicts the likelihood of heart disease, providing the

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information on the health condition of the user. This allows for early diagnosis and preventive health care.

- **Outcome:** The interactive system simplifies the decision-making process for healthcare professionals by providing predictive insights. This data-driven way of doing things helps in making informed healthcare decisions and can be integrated to broader healthcare systems for preventive healthcare.

4.3 Interface of the Web-Based System

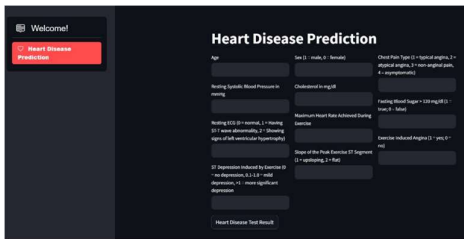


Figure 7 Interface with No Input

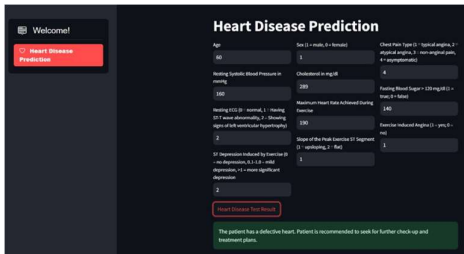


Figure 8 Output: Defective Heart

The final heart disease detection web-based system is shown in Figure 7. At this stage, no input values have been entered. The user is required to key in relevant health information like age, sex, blood pressure and cholesterol and other parameters as it has been presented. After the data is entered by the user, there is an option to click the 'Heart Disease Test Result' button to be given a prediction whether the user is at risk of suffering from heart disease or not. By integrating the trained model in Streamlet, the web system enables real-time prediction based on inputs of the user, which allows for efficiency and convenience. The system's interface is intuitive, and the results are presented instantly, proving the machine learning model's applicability in the support of clinical decision making. Figure 8 illustrates the interface

after inputting sample health data. Upon clicking the "Heart Disease Test Result" button, the system returns a prediction indicating that the user has a normal heart. Figure 8 shows another instance where a different set of health values has been entered. In this case, the system predicts a defective heart, highlighting the model's capability to detect potential risk based on the user's clinical inputs. A message is also displayed to alert patient to seek further check-up and treatment plans.

4.4 Functionality and User Workflow

The user workflow process begins when the user enters values into each of the input fields, such as age, cholesterol level, whether they experience exercise-induced angina and other values. Once all the required data is provided, the user clicks the "Heart Disease Test Result" button. The system then sends these inputs to the backend model, which processes the input vector and generates a binary classification where 0 indicates no heart disease and 1 indicates the presence of heart disease. Finally, the result is displayed clearly on the web interface, showing whether the user has a healthy or defective heart.

4.5 System Testing

The heart disease detection system was extensively tested and validated using the same dataset in which it was trained. The dataset has a target column which states whether an individual is likely to suffer from heart disease or not. The target column was used as a benchmark for comparing the accuracy of the output of the model, in this way, ensuring that the results provided by the system match the actual heart disease diagnosis. The results showed the system achieving accuracy of 97% of the respondents, indicating that 97% of the predictions made by the model were proved to be correct. This means that the model is highly effective in predicting whether an individual has heart disease or not. The other 3% of predictions were inaccurate, positive being false and false negatives.

4.6 System Validation

In order to assess the usability and effectiveness of the developed heart disease detection system, a structured Google Form questionnaire was created and sent to two key user groups: IT professionals and healthcare professionals. The participants were asked to test the web-based system and provide feedback to different aspects of the system. The survey was carefully created to evaluate various aspects of the system including system usability, accuracy of predictions, technical performance, user interface and clarity of the generated results by system. Most of the questions used a Likert scale format ranging from 1 to 5,

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where 1 indicated "strongly disagree" and 5 indicated "strongly agree." In addition to the scaled questions, open-ended questions were also included to collect more detailed feedback and suggestions. The gathered answers provided meaningful insights in terms of technical and clinical relevance of the application.

Category	Summary / Result
Total Respondents	10
Average Years of Experience	3.7 years
System Stability	8.7
Web Interface Responsiveness	8.5
Prediction Speed	8.5
Design Suitability for Healthcare	8.3
Clarity of Output	8.5
Common Technical Recommendations	- Add clear error messages for invalid inputs - Improve data security - Refine design
Job Titles of Respondents	Developers, IT Support, Help Desk, Technician

Table 6 Results of Feedback from IT professionals

Category	Summary / Result
Total Respondents	10
Average Years of Experience	7.8 years
System Navigation & Usability	9.4
Clarity of Input Fields	9.3
Interpretability of Results	9.0
Relevance of Selected Health Factors	9.0
Common Suggestions	-Make interface more user-friendly -Improve accuracy or explain prediction basis -Provide more

	descriptive result output
Job Titles of Respondents	Doctors, GPs, Lecturers, Associate Professor (clinical focus)

Table 7 Results of Feedback from healthcare professionals

Table 6. IT professionals focused on the stability of the system, usability, and technical suggestions, like handling errors and data security. They highly scored the system in terms of stability and clarity. On the other hand, Table 7. healthcare professionals highlighted the user-friendliness of the interface and ease to comprehend the results. They suggested the improvement in terms of the interpretability of the results and the use of more descriptive output, focusing on the presentation of information to healthcare professionals.

4 CONCLUSION

This research successfully met its aim of at developing a web-based heart disease detection system that uses machine learning algorithms to provide the probability of heart disease dependant on many health indicators. The system was tested against numerous machine learning models and ultimately selected Random Forest model as the best performing model. The outcomes, discussed in the *Results and Discussion* chapter, confirmed the effectiveness of the system in terms of accuracy, precision, recall, and F1-score, fulfilling the initial research objectives.

Despite the achievements, a number of limitations were found in this study. The use of a set of static data is a major limitation. This is because the data might not describe the difference and diverse nature of the population. Furthermore, the problem of interpretability of the model continues to exist, since some users, particularly healthcare professionals, wanted a more detailed description of the prediction background. The following insights concluded that the system has a good starting point but requires future refinement to improve.

There are several rooms of improvement for the system in future research. An inclusion of primary data from practical clinical settings is one of the main recommendations. Application of publicly available datasets for training the models has its limitations, especially upon assessing the diversity of the population. With the use of primary data, the system could be trained with more recent and more comprehensive information allowing it to be more accurate concerning applicability to

other patient groups. Also, the introduction of this system in working with mobile applications may also dramatically enhance its accessibility and ease of use for the users.

The study of advanced algorithms is another area for which future studies could be conducted. Although the algorithms evaluated in the present study were quite successful, a deep learning approach or ensemble method may still be applied to increase predictive value of the system, particularly if the data are less straightforward. These methods may support the better generalization and processing of large and varied health datasets. Along with this, further research can be conducted on personalized predictions using other factors, which may include genetic and family history, and a person's lifestyle. Thus, this could enable the system to give personalized and more accurate predictions. This would make it a better system in personalized healthcare.

Finally, the heart disease detection system designed in this research work has shown promise in making quick and effective heart disease prediction using health data. However, there are multiple aspects of improvements: integration of primary data, mobile application support, advanced algorithms and improved UX. By targeting these aspects in further research, the system may become more advanced in its practical use for the detection of heart disease alerting both healthcare workers and the public.

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