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Explainable Artificial Intelligence for Clinical Decision Support in Precision Healthcare Systems

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Abstract

The use of Artificial Intelligence (AI) in healthcare has become a growing trend to help clinicians in disease diagnosis, forecasting patient outcomes, and enhancing treatment planning. A significant portion of the highly developed machine learning models can be viewed as black-boxes, and the decision-making process in healthcare is hard to comprehend how the prediction is made. This non-transparency has the potential to reduce the AI implementation in the clinical setting where interpretability and trust are crucial. To eliminate this difficulty, Explainable Artificial Intelligence (XAI)., has turned out to be an enticing solution that boosts the openness and readability of AI models. This study will put forward an explicable AI-based framework in clinical decision support in precision healthcare systems that will predict heart disease by using clinical patient data. The dataset used in the study is the Heart Disease Cleveland of the UCI Machine Learning Repository that presents clinical features including age, sex, type of chest pain, blood pressure, cholesterol, electrocardiographic findings, and maximum heart rate. Healthcare professionals usually use these characteristics to estimate cardiovascular health. Within the proposed method, data cleaning, normalization, and feature selection are performed on the dataset to guarantee quality and consistency of data. Machine learning algorithms are subsequently created to determine whether a patient is at risk of having heart disease based on the given clinical characteristics.

Keywords: Explainable Artificial Intelligence (XAI), Clinical Decision Support Systems, Precision Healthcare, Heart Disease Prediction, Machine Learning in Medical Care and Medical Data Analytics

1.Introduction

Artificial intelligence has emerged as one of the most disruptive technologies in modern healthcare, enabling advanced data processing, predictive modeling, and intelligent decision support. The rapid growth of healthcare data, including electronic health records, clinical measurements, wearable sensor outputs, and medical imaging, has created substantial opportunities for the deployment of AI-driven systems in diagnosis, prognosis, and treatment planning [1-3]. Machine learning algorithms can analyze large-scale and high-dimensional patient data to uncover latent patterns and associations that may not be readily detectable through conventional clinical assessment alone [4-6]. As a result, AI-based technologies are increasingly being integrated into healthcare systems to improve diagnostic accuracy, operational efficiency, and patient outcomes [7-9].In recent years, AI has shown considerable promise in the prediction and early detection of chronic diseases such as cardiovascular disease, diabetes, and cancer [10-12]. Cardiovascular disease, in particular, remains one of the leading causes of mortality worldwide, making early diagnosis and timely risk stratification essential for improving survival and reducing complications [13-15]. Machine learning models can process key clinical variables, including blood pressure, cholesterol level, electrocardiographic findings, heart rate, and other patient-specific indicators, to estimate disease risk and support earlier intervention [16-18]. Such capabilities position AI as a valuable component of next-generation clinical care, where data-driven insights can complement physician expertise.Clinical Decision Support Systems are computer-based intelligent platforms designed to assist healthcare professionals in making informed clinical decisions. These systems analyze patient data and generate recommendations that support diagnosis, treatment planning, and disease risk assessment [19-21]. With the incorporation of modern data analytics and machine learning techniques, CDSS can examine large volumes of medical information and identify clinically meaningful patterns that enhance decision quality [22-24]. Consequently, these systems play an important role in improving healthcare delivery, reducing medical errors, and strengthening patient safety [25].CDSS has become increasingly important in the broader context of precision healthcare. Precision healthcare emphasizes individualized medical care based on patient-specific characteristics such as genetic profile, lifestyle, environmental exposure, and medical history, rather than relying on a uniform treatment strategy for all patients. This personalized approach can improve therapeutic effectiveness and reduce adverse outcomes by aligning care decisions with the unique profile of each individual. AI-powered CDSS is particularly well suited to this paradigm because it can integrate diverse patient-centered data sources to identify risk factors, estimate disease progression, and recommend tailored treatment strategies.Despite these advantages, the integration of artificial intelligence into clinical decision support systems remains associated with important challenges. Many machine learning models used in healthcare prediction are highly complex and function as black-box systems. Although these models may achieve high predictive performance, their internal decision processes are often difficult for clinicians to interpret. This lack of transparency can reduce trust in AI-generated recommendations and hinder adoption in real-world medical settings, where accountability, safety, and clinical justification are essential.

2.Literature Review

Artificial intelligence has become an important component of modern healthcare by enabling advanced analysis of medical data and supporting clinical decision-making processes [26-28]. The rapid growth of healthcare information, including electronic health records, diagnostic imaging, laboratory findings, and wearable device data, has created strong opportunities for the application of machine learning methods in disease detection and patient management [29-31]. AI-based models can process large and complex datasets to identify hidden patterns that may not be immediately apparent to healthcare professionals. These capabilities allow healthcare systems to support earlier disease detection, anticipate health risks, and recommend more appropriate treatment strategies [32-34].Machine learning algorithms have been widely applied to the prediction of various diseases, including cardiovascular disorders, diabetes, cancer, and neurological conditions [35-37]. By analyzing patient-specific attributes such as age, blood pressure, cholesterol level, lifestyle factors, and clinical test results, AI systems can identify patterns associated with disease risk and progression. Such predictive models can assist clinicians in estimating the likelihood of disease occurrence and in designing preventive healthcare interventions [38,39]. Among these applications, cardiovascular disease prediction has received particular attention because heart disease remains one of the leading causes of death worldwide. Machine learning models can simultaneously evaluate multiple clinical variables and generate accurate predictions regarding whether a patient has heart disease or is at elevated risk of developing it [40].A wide range of machine learning algorithms has been used in healthcare prediction, including logistic regression, decision trees, support vector machines, random forests, and neural networks. These approaches differ in terms of complexity, interpretability, and predictive performance. Simpler models, such as logistic regression and decision trees, are often considered more suitable for clinical settings because their outputs are easier to interpret. In contrast, more complex models, particularly deep learning methods, may achieve higher predictive accuracy but frequently lack transparency.Despite the growing success of AI-based healthcare prediction systems, several important challenges remain. Data quality issues, model reliability, and ethical considerations continue to affect real-world adoption. Medical datasets are often incomplete, imbalanced, or limited in size, which can negatively influence model performance and generalizability. In addition, AI systems must be rigorously validated before being deployed in clinical practice to ensure safety, robustness, and trustworthiness. Addressing these limitations is essential for the effective integration of AI technologies into healthcare systems and for improving the reliability of predictive models in clinical decision support.

3. Methodology

This study deploys a machine learning approach in order to create a predictive model to detect heart diseases through clinical patient information. The Heart Disease Cleveland dataset is considered the main source of data, consisting of several medical characteristics of cardiovascular diseases [41]. Preprocessing Data cleaning, normalization, and feature scaling are used in data preprocessing in order to prepare the dataset to be analyzed. Exploratory data analysis is performed to get the connection of features and the relationship among the variables. The Support Vector Machine (SVM) algorithm is applied to the patients in order to distinguish between those with and without heart disease [42]. To determine the accuracy of classification and predictive reliability of the model performance it is assessed using confusion matrix and ROC curve.

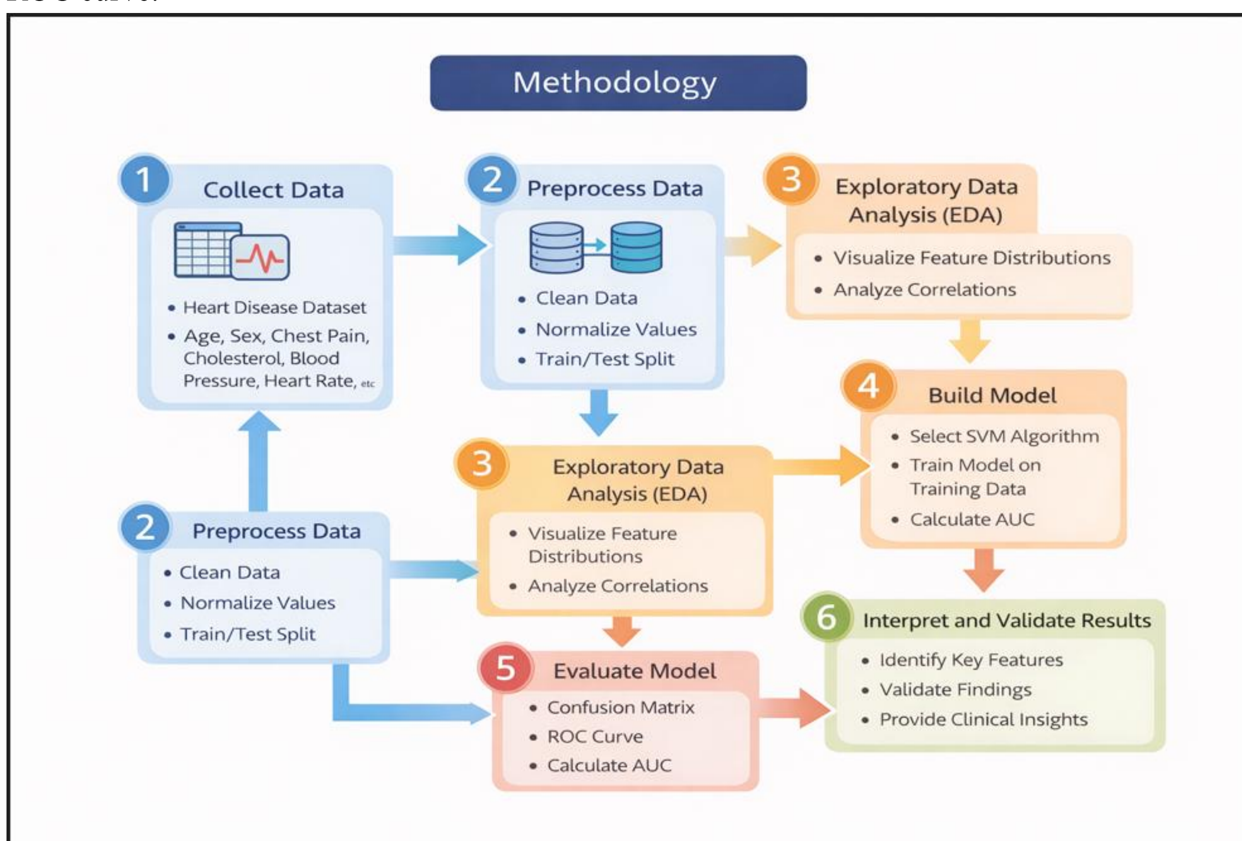

Figure 1: This diagram illustrates the process of heart disease prediction with machine learning

The methodology diagram shows how a machine learning model of predicting heart disease was developed in a systematic manner. It starts with data collection whereby the patient data collected in a clinical setting (age, sex, chest pain type, cholesterol level, blood pressure and heart rate) is obtained in the heart disease data set. The second step is data preprocessing, which consists of the processing of the data (cleaning, normalization of the values, the division of the data into training and test sets). The next step is the exploratory data analysis (EDA), which is used to visualize the distributions of features and investigate the correlation between variables. The model building phase uses the Support Vector Machine (SVM) algorithm in the training of

the predictive model [43]. Performance measures are then used to assess the model which include the confusion matrix and ROC curve. Lastly, the outcomes are analyzed to determine the major characteristics and offer clinical information to support decision-making.

3.1 Dataset Description

The dataset of this study is Heart Disease Cleveland dataset which is received at UCI Machine Learning Repository. This data set includes clinical data obtained concerning patients who have gone through cardiovascular checkups. It entails different demographic, physiological, and diagnostic factors which are usually applied by health care providers in determining the risk of heart diseases [47] (*Figure 1*). The data set includes 303 patient records which have 13 clinical attributes and also a target variable (presence or absence of heart disease). The age, sex, type of chest pain, blood pressure during resting, level of serum cholesterol before and after exercise, results of fasting blood sugar, results of resting electrocardiographic, maximum amount of heart rate during exercise, angina caused by exercise, ST depression caused by exercise, slope of the ST segment, number of major vessels colored by fluoroscopy and thalassemia tests are some of the major features in the dataset. The target variable, which is condition, will be used to show whether a patient has heart disease [48]. The value 0 means that an individual does not have heart disease whereas a 1 value means that an individual has heart disease.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	condition
2	69	1	0	160	234	1	2	131	0	0.1	1	1	0	0
3	69	0	0	140	239	0	0	151	0	1.8	0	2	0	0
4	66	0	0	150	226	0	0	114	0	2.6	2	0	0	0
5	65	1	0	138	282	1	2	174	0	1.4	1	1	0	1
6	64	1	0	110	211	0	2	144	1	1.8	1	0	0	0
7	64	1	0	170	227	0	2	155	0	0.6	1	0	2	0
8	63	1	0	145	233	1	2	150	0	2.3	2	0	1	0
9	61	1	0	134	234	0	0	145	0	2.6	1	2	0	1
10	60	0	0	150	240	0	0	171	0	0.9	0	0	0	0
11	59	1	0	178	270	0	2	145	0	4.2	2	0	2	0
12	59	1	0	170	288	0	2	159	0	0.2	1	0	2	1
13	59	1	0	160	273	0	2	125	0	0	0	0	0	1
14	59	1	0	134	204	0	0	162	0	0.8	0	2	0	1
15	58	0	0	150	283	1	2	162	0	1	0	0	0	0
16	56	1	0	120	193	0	2	162	0	1.9	1	0	2	0
17	52	1	0	118	186	0	2	190	0	0	1	0	1	0
18	52	1	0	152	298	1	0	178	0	1.2	1	0	2	0
19	51	1	0	125	213	0	2	125	1	1.4	0	1	0	0
20	45	1	0	110	264	0	0	132	0	1.2	1	0	2	1
21	42	1	0	148	244	0	2	178	0	0.8	0	2	0	0
22	40	1	0	140	199	0	0	178	1	1.4	0	0	2	0
23	38	1	0	120	231	0	0	182	1	3.8	1	0	2	1
24	34	1	0	118	182	0	2	174	0	0	0	0	0	0
25	74	0	1	120	269	0	2	121	1	0.2	0	1	0	0
26	71	0	1	160	302	0	0	162	0	0.4	0	2	0	0
27	70	1	1	156	245	0	2	143	0	0	0	0	0	0
28	66	1	1	160	246	0	0	120	1	0	1	3	1	1
29	63	0	1	140	195	0	0	179	0	0	0	2	0	0
30	62	1	1	120	281	0	2	103	0	1.4	1	1	2	1
31	62	1	1	128	208	1	2	140	0	0	0	0	0	0
32	59	1	1	140	221	0	0	164	1	0	0	0	0	0
33	58	1	1	120	284	0	2	160	0	1.8	1	0	0	1
34	58	0	1	136	319	1	2	152	0	0	0	2	0	1
35	57	0	1	130	236	0	2	174	0	0	1	1	0	1
36	57	1	1	124	261	0	0	141	0	0.3	0	0	2	1
37	57	1	1	154	232	0	2	164	0	0	0	1	0	1
38	56	1	1	120	240	0	0	169	0	0	2	0	0	0

heart_cleveland_upload

Figure 1 :(Source Link: https://www.kaggle.com/datasets/cherngs/heart-disease-cleveland-uci)

3.2 Data Preprocessing

Preprocessing of data is a necessary process of preparing the data to be analyzed using machine learning. The raw data can also have inconsistencies, missing values or aspects that need to be transformed first before it can be effectively used by predictive models. In this research, various preprocessing methods have been used in order to get good quality of the data

and enhance the performance of the model [50]. First, the data were analyzed to determine gaps in the data or irregularities in the clinical characteristics. Missing or invalid values were appropriately addressed so that the data set could be used to analyze it. The workflow of data cleaning followed by standardization of the numerical features was done so that the attributes with bigger scales did not dominate the learning process of the machine learning algorithm. Normalization and scaling of the features were done to make the data fall within a common range which becomes important especially with algorithms like the Support Visualization Machines [51]. The data were standardized using the standardization methods to transform it into normalized data whose mean is zero and a standard deviation of one. Besides the normalization, the dataset was split into training and testing sets. The predictive model was constructed using the training dataset and the performance of the model was assessed using the testing dataset. This division assists in making sure that the model is applicable and does not overfitting.

3.3 Development of machine learning model

This was research that employed the Support Vector Machine (SVM) algorithm in creating the predictive model to be used in heart disease classification. SVM is a machine learning model that is well applied in classification problems because it has the capacity to identify the best decision boundaries between classes, which is supervised. The SVM model operates as follows: It finds a hyperplane dividing the data points of the two classes. The algorithm will be designed to maximize the distance between the two classes thus enhancing accuracy and strength of classification. SVM is efficient especially in those cases when one works with multiple features and complex relationships in the dataset. The SVM classifier was trained on the training dataset at the stage of model development [55]. The algorithm was taught patterns and relationships among clinical characteristics and the existence of heart disease. The trained model was then used on the test data to test its predictive power. The application of SVM in the study enables the model to establish the intricate relationships between clinical variables and produce credible results of classification [56]. The healthcare prediction task can be approached with the algorithm because it has the capacity to present high-dimensional data.

3.4 Model Evaluation and Performance Measures

To assess the predictive power of the machine learning model, a set of classification measures were used to measure the performance of the model (***Figure 2)***. Evaluation metrics present quantitative measures which are used to determine the effectiveness of the model in terms of prediction of heart disease cases. The analysis of the classification results was conducted through the confusion matrix applied to compare the prediction labels to actual patient conditions. This matrix gives the information concerning true positives, true negative, false positives, and false negatives. These values assist in assessing the accuracy of the model and determining possible errors of classification [57]. Besides the confusion matrix, the Receiver Operating Characteristic (ROC) curve was employed in the assessment of the capability of the

model to differentiate between heart disease and disease-free patients. The ROC curve represents a graph that shows a relationship between the true positive rate and false positive rate at various classification thresholds. The result of Area under the Curve (AUC) of the ROC analysis shows the overall classification performance of the model. The larger the AUC value, the higher the predictive ability is. The combination of these evaluation measures will help the study to assess the predictive model holistically and give valid results that can be used to make clinical decisions.

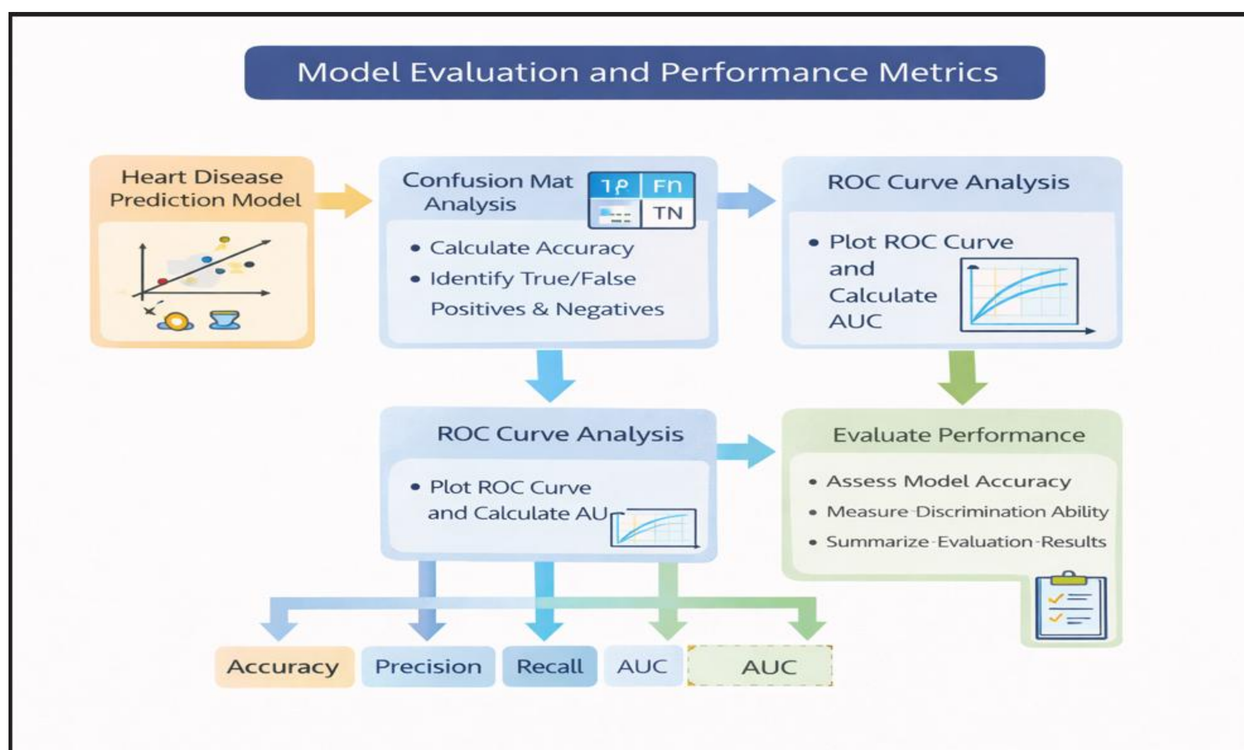

Figure 2: The diagram illustrates the process of evaluating a machine learning model of predicting heart disease

The diagram shows how it is possible to assess the performance of a heart disease prediction model based on machine learning methods [57]. This is initiated by the heart disease prediction model which produces classification outputs given the clinical data of the patients. The second step is that of confusion matrix analysis whereby the prediction of the model is matched to actual results and the accuracy attained is determined and true positives, true negatives, false positives, and false negatives are identified [58]. This is followed by curve analysis of ROC to visualize the model capability to discriminate between the classes and calculate the area under the curve (AUC). Lastly, the model performance is measured based on some key measures such as the accuracy, precision, recall AUC that summarize the efficiency and reliability of the predictive model.

3.5 Conceptual Framework

The theoretical backbone of the proposed research is the combination of machine learning methods and explainable artificial intelligence (XAI) to assist clinical decisions in accurate healthcare systems (***Figure 3)*** . The model should examine patient clinical data, and create a predictive model that can determine the risk of heart disease but give understandable results to the healthcare personnel. The framework comprises a few interdependent parts such as data input, data preprocessing, and development of machine learning model, explainability analysis, and clinical decision support. The initial element of the framework will entail the gathering of the clinical patient data of the Heart Disease Cleveland dataset. This data set has different attributes of medicine like age, sex, the type of chest pain, level of cholesterol, the pressure at rest, the highest heart rate during exercise, and other diagnostic criteria that are usually applied in cardiovascular analysis [2]. These characteristics are input variables that can give a basis to the prediction analysis. The second subdivision is the data preprocessing that provides that the dataset is correctly prepared to undergo machine learning analysis. Data cleaning, treatment of missing values, numeric feature normalization, and dividing the dataset into training and testing groups are some of the tasks that are carried out in this stage [3]. Preprocessing enhances better quality and uniformity of the data, enabling machine learning algorithms to gain insightful patterns of the data. The third part is the creation of the predictive framework based on a Support Vector Machine (SVM) algorithm.

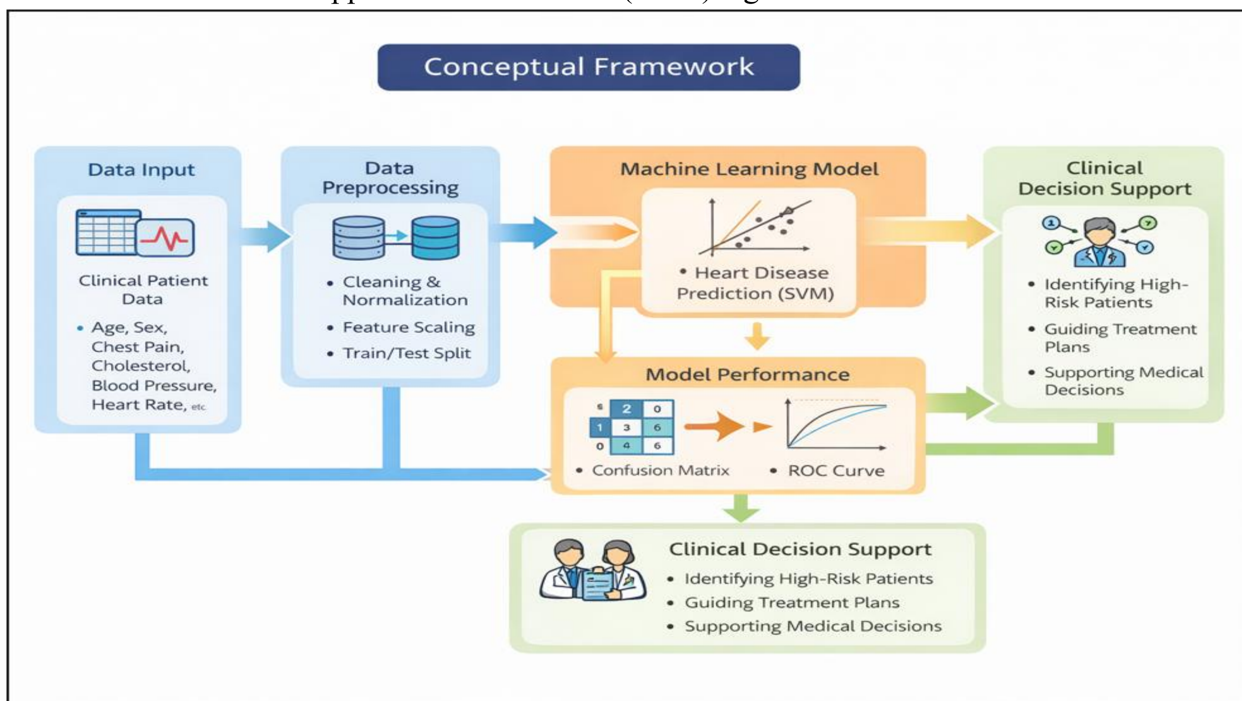

Figure 3:This diagram illustrates the process of evaluating a machine learning model of predicting heart disease

The diagram shows how it is possible to assess the performance of a heart disease prediction model based on machine learning methods. This is initiated by the heart disease

prediction model which produces classification outputs given the clinical data of the patients. The second step is that of confusion matrix analysis whereby the prediction of the model is matched to actual results and the accuracy attained is determined and true positives, true negatives, false positives, and false negatives are identified [6]. This is followed by curve analysis of ROC to visualize the model capability to discriminate between the classes and calculate the area under the curve (AUC). Lastly, the model performance is measured based on some key measures such as the accuracy, precision, recall AUC that summarize the efficiency and reliability of the predictive model.

4. Results

The outcome of this study proves that the proposed machine learning solution is effective to predict heart diseases based on the provided clinical data (***Figure 4)***. Exploratory data analysis has shown some significant trends in patient characteristics including age, cholesterol, blood pressure, type of chest pain, and the highest heart rate. The correlation and distribution analysis assisted in determining the clinical characteristics that were significant in determining cardiovascular risk. The Support Vector Machine (SVM) model was applied to categorize patients who had heart diseases or not. The results of the confusion matrix show that there were quite many correct classifications and few misclassifications. Also, analysis of the ROC curve gave an AUC of around 0.83, which is a good predictor and has good classification ability.

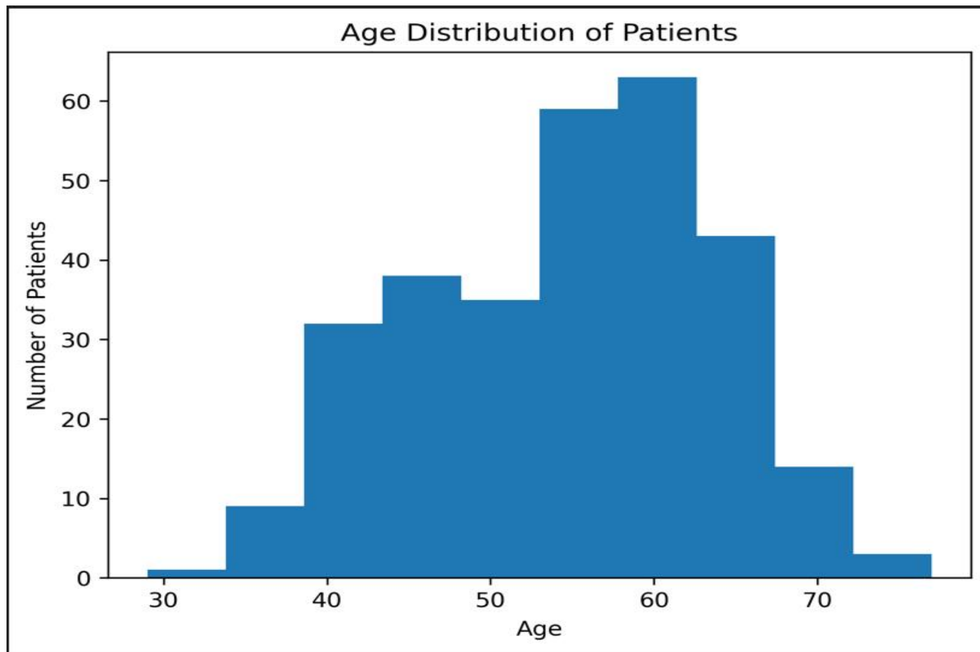

Figure 4: This image displays the distribution of patient ages in the dataset of heart disease

The distribution of the patient age used in this study is displayed in Figure 1 to be used in a heart disease dataset. The histogram will depict the distribution of the population of patients in the various age categories and will give a picture of the demographics of the data used. The horizontal line is used to show the age of the patients and the number of people falling in each

age group is shown in the vertical line. According to the visualization, the dataset mostly includes the patients of the age between about 40 and 65 years. The maximum number of patients is concentrated between 50 and 60 years, which means that the majority of the data include the middle-aged population.

Correlation of cholesterol and peak heart rate

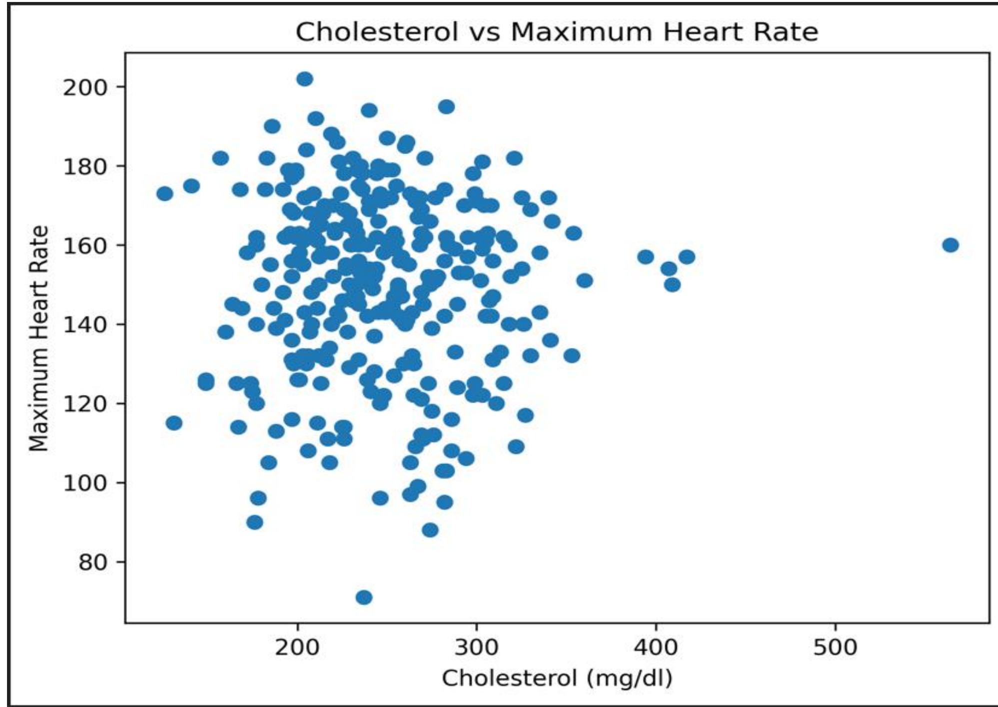

Figure 2: This image shows dependence between cholesterol level and maximum heart rate.

Figure 2 shows the correlation between the serum cholesterol level and the peak heart rate attained during exercise in patients in the heart disease dataset. The scatter plot is a graphic representation of the single patient observations in which the horizontal axis represents the cholesterol levels in the body expressed in milligrams per deciliters (mg/dl) and the vertical axis expresses the maximum heart rate at maximum physical activity. Every value on the graph represents one patient record, and it is possible to visualize the trends or patterns between these two clinical variables. According to the distribution of points, it can be seen that the majority of patients are positioned in the range of cholesterol between 180 and 320 mg/dl, and the maximum heart rate values of the patients are usually within the range of 110-180 beats per minute. The clustering of the points within this area depicts that a large percentage of patients show moderate cholesterol levels and moderate to high maximum heart rates during exercise testing.

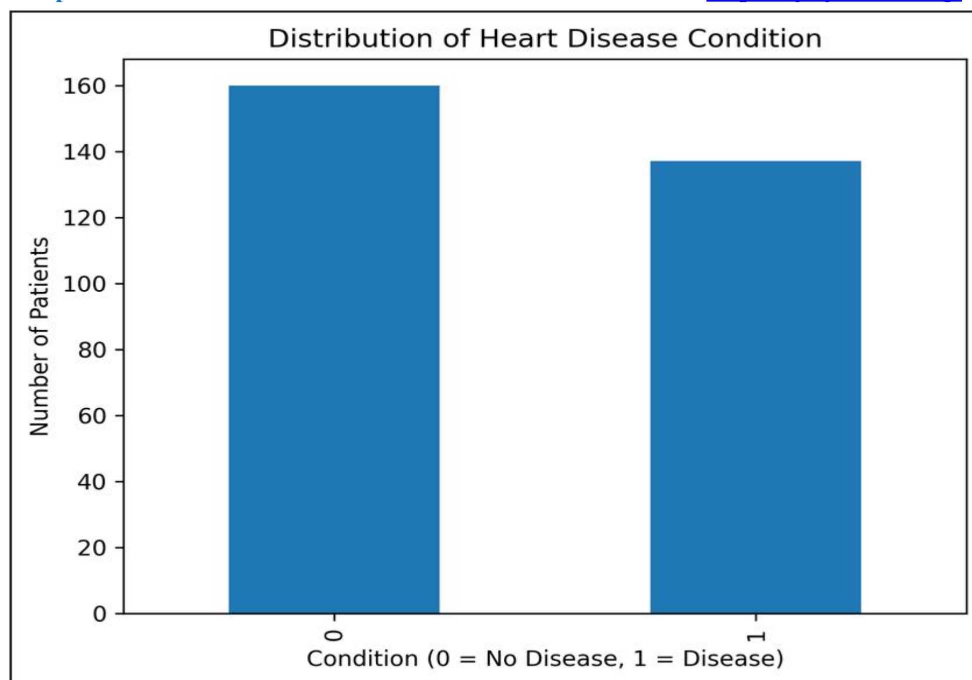

Figure 3: This image illustrate patients with and without heart disease distribution

The data in figure 3 shows the distribution of the heart disease conditions in patients used in the dataset in this study. The bar chart shows the population grouped into two groups according to the target variable named condition where the category 0 shows the patients who have not been diagnosed with heart disease whereas the category 1 shows patients with heart disease. The vertical axis is the summation of the overall number of patients per category whereas the horizontal axis indicates the disease condition classification. Based on how the visualization looks, it is possible to notice that the count of patients without heart disease is a little higher than that of the patients who have heart disease. In particular, the sample has about 160 heart diseases-free and about 137 heart disease patients. Such a fairly equal ratio of the two classes is a noteworthy property of machine learning use since balanced data sets can be used to lower biases in predictive models and enable algorithms to discover significant patterns across the two classes .

4.2 Correlation Analysis of Clinical Characteristics

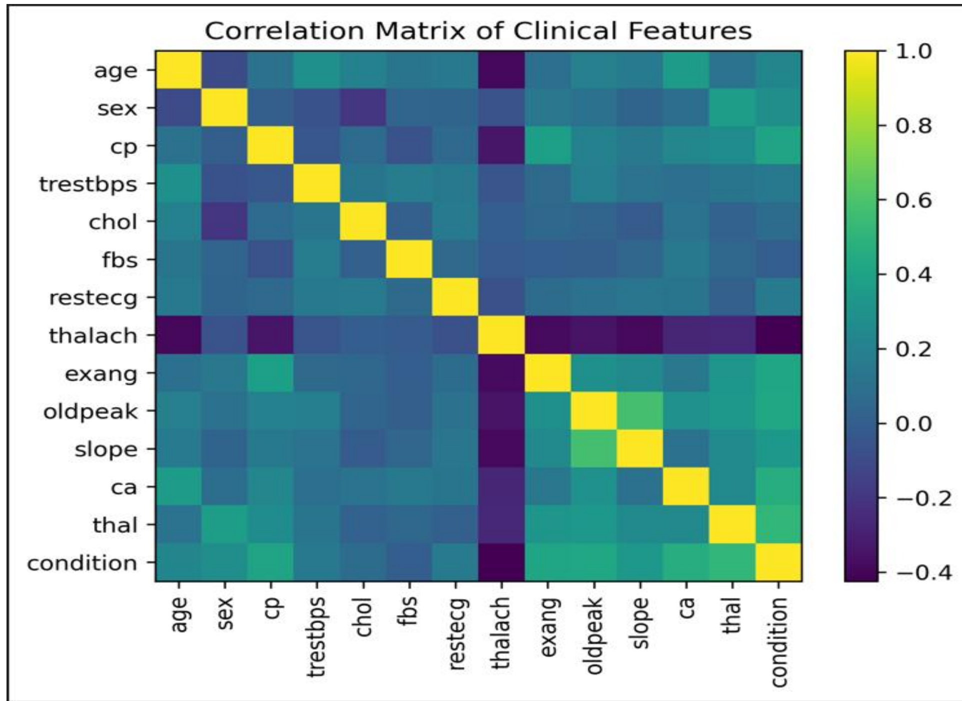

Figure 4: This image displays the correlation between clinical characteristics in prediction of heart disease

Figure 4 describes the correlation diagram of the clinical variables that are incorporated in the dataset of heart disease considered in this study. The heatmap can graphically illustrate the relationship between the various variables; it can show the correlation coefficients between the variables both negative and positive. The matrix cells show the strength and direction of the relationship between two attributes of clinical aspects. A warmer color normally depicts high positive correlations and colder or darker colors depict weak or negative correlations. The diagonal items of the matrix show a value of perfect correlation of 1.0 since each variable is perfectly correlated to itself. As per the visualization, we can note that there are a number of clinical attributes that are moderately related to the target variable denoted as condition, and it is the presence or absence of heart disease. Chest pain type (cp), exercise induced angina (exang), ST depression caused by exercise (oldpeak), number of major vessels coloured by fluoroscopy (ca), test results on thalassemia (thal) are variables that are associated with the disease condition in a relatively stronger relationship than the other attributes.

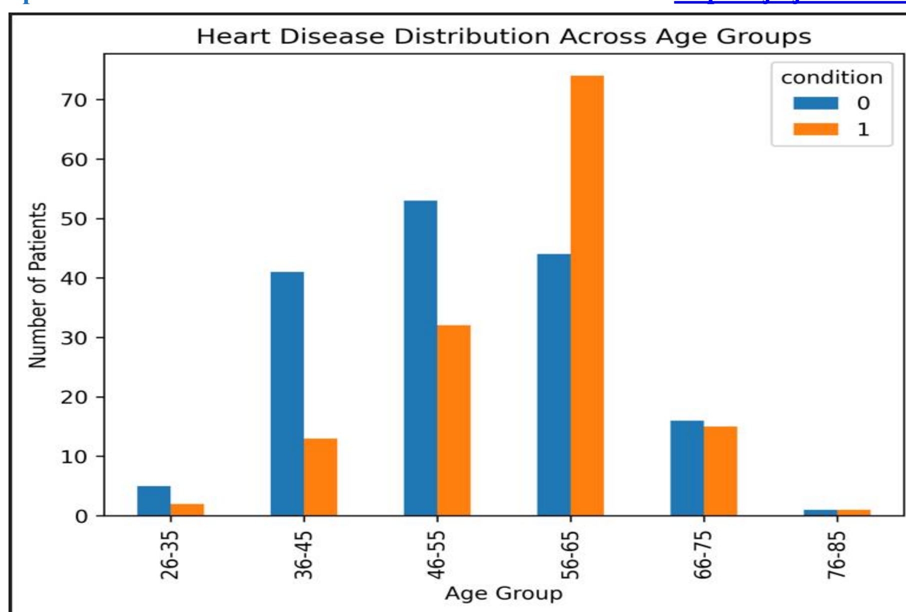

Figure 5: This image shows the prevalence of heart diseases in various age groups of patients

Figure 5 shows the distributions of cases of heart disease among the various age groupings of the dataset that was used in this study. The bar chart will divide the patients into 6 age groups, i. e. 26-35, 36-45, 46-55, 56-65, 66-75, 76-85 years. There are two bars in every age group that apply to the number of patients with no heart disease (condition = 0) and the number of patients with heart disease (condition = 1). The total number of patients in each category is the vertical axis, and the horizontal axis is the age groups. With the visualization, one can note that the prevalence of heart disease is higher with old age, especially in people between 46 and 65 years. The greatest incidence of heart diseases is seen in the age population of 56–65 years where the cases of patients diagnosed with heart disease are very high compared to the cases of patients not diagnosed with heart disease. This finding implies that people in this age group are susceptible to cardiovascular disorders which is in line with medical established facts that risk of heart diseases increases with age as a result of physiological changes, lifestyle and accumulation of cardiovascular risk factors.

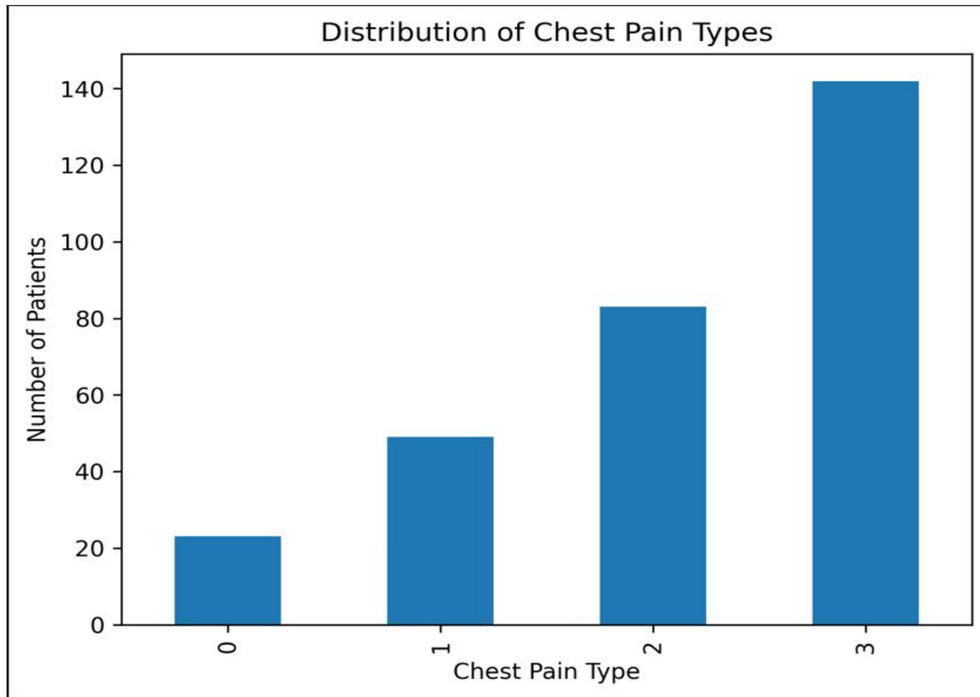

Figure 6: This image depicts the distribution of the various types of chest pain in the patients

Figure 6 shows how the type of chest pain was distributed among the heart disease dataset patients, who participated in this research. The bar chart groups patients according to the attribute of the chest pain (cp) that defines the various types of the symptoms of chest pain that are usually assessed in cardiovascular diagnosis. The four categories of chest pain identified as 0, 1, 2 and 3 appear in the horizontal axis, with the number of patients observed in each of the categories appearing in the vertical axis. These types of categories are clinically identified types of chest pain such as typical angina, atypical angina, non-anginal pain and asymptomatic. Based on the visualization, it is possible to note that the number of patient cases in chest pain type 3 is the largest, which indicates that silent symptoms or asymptomatic chest pain is a common occurrence among the data. The observation is significant since cases that are asymptomatic might not have such red flags that are easy to notice hence, early detection of heart diseases becomes difficult. The second most prevalent one is chest pain type 2, and type 1 and type 0 which have relatively less patients [18]. The comparatively less number of patients in category 0 and 1 indicate that the common and uncharacteristic symptoms of angina are underrepresented in the dataset as opposed to non-anginal and no symptoms recorded. In clinical terms, the characteristics of chest pain are regarded as being among the most significant predictors that the doctors use to assess the cardiovascular condition. Chest pains of different kinds can indicate different degrees of heart risk and heart anomalies [19].

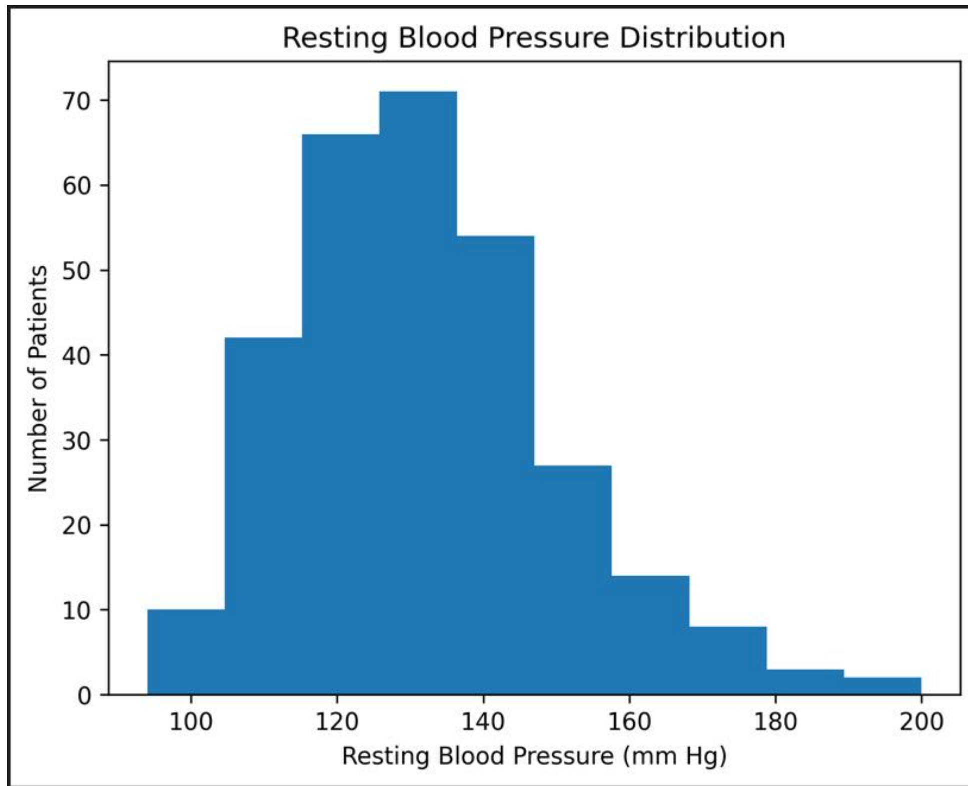

Figure 7: This image demonstrates distribution of the values of Resting blood pressure of patients.

Figure 7 shows the distribution of the values of the resting blood pressure of patients incorporated in the heart disease dataset utilized in this study. The histogram is the count of the frequencies of patients given the various ranges of resting blood pressure in millimeters of mercury (mm Hg). The horizontal line shows the values of the resting blood pressure and the vertical line shows the number of patients in respective ranges. Based on the visualization, one can see that most of the patients are in the range of blood pressure of 110 mm Hg to 150 mm Hg. The concentration of the number of observations of the patients is greatest within the range of 120-140 mm Hg, which indicates that a majority of the patients in the dataset have a moderate level of resting blood pressure. This distribution is in line with the common clinical findings where there are a lot of persons undergoing cardiovascular check-up that reveal a borderline or moderately high level of blood pressure. Also, the chart indicates that the number of patients who are in the lower blood pressure scales such as those under 110 mm Hg is lower, on the other hand, a few of the patients have much higher resting blood pressure at above 160 mm Hg.

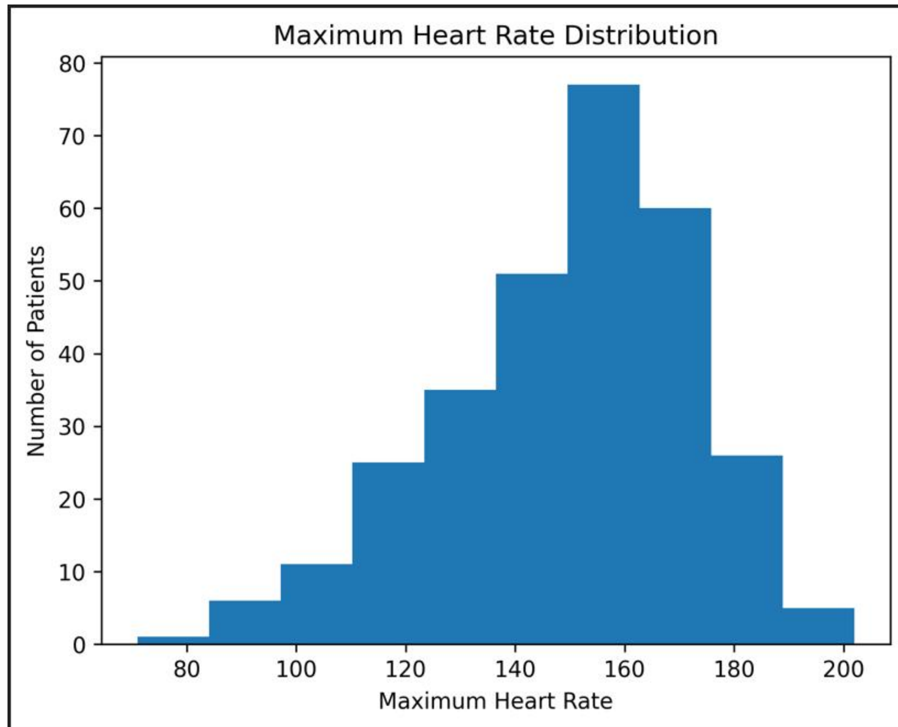

Figure 8: This image represents the distribution of maximum heart rate values of patients

Figure 8 shows the graph (maximum heart rate) of values attained by the patients during exercise testing in the dataset employed in this study. The histogram shows the frequency of patients within the various intervals of maximum heart rates giving a picture of cardiovascular performance among those that were selected in the dataset. The top line in the horizontal analysis indicates the highest possible values of heart rate, whereas the left axis shows the number of patients who fit in each range. Based on the visualization, one can see that most patients reach maximum values of heart rate in the range of 130 -170 beats per minute. The mode of the observations is in the 150-160 beats per minute range, indicating that a big part of the data has moderate to fairly high heart rate responses to exercise. This trend is a normal physiological behavior, as the heart rate rises as a result of physical activity to supply the body with oxygen. Further, the chart indicates that a comparatively smaller number of patients are in the lower maximum heart rate ranges of less than 110 beats per minute which could be due to either reduced cardiovascular response or impaired exercise capacity. This may sometimes be linked to existing heart conditions, poor physical fitness or other physiological restrictions such as lower heart rate responses during stress testing.

4.3 SVM Model Performance Analysis

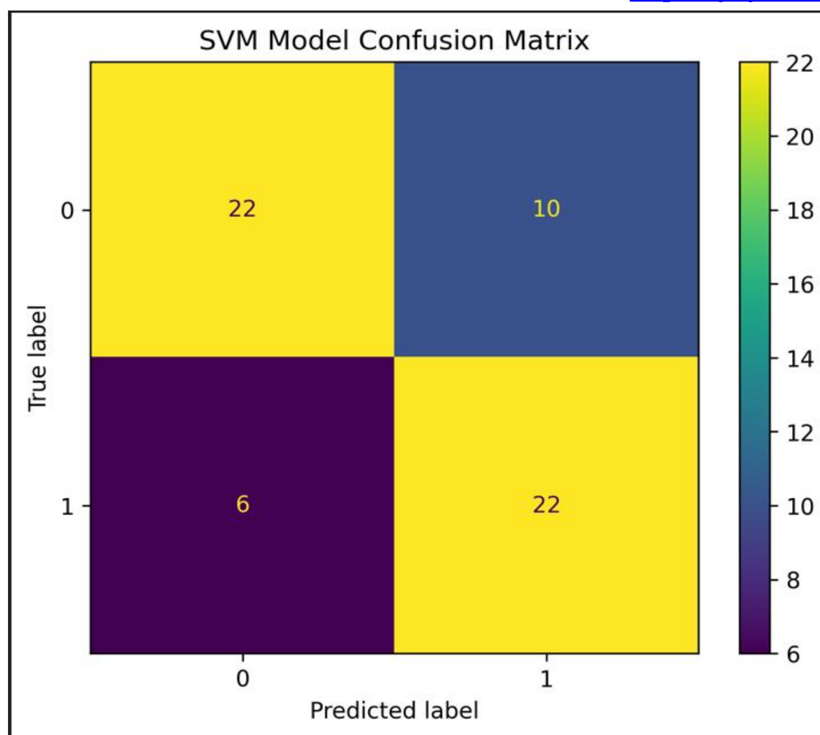

Figure 9: This image shows the performance of the SVM heart disease prediction model in terms of classification

Figure 9 shows the confusion table of the Support Vector Machine (SVM) model on prediction of heart disease. The confusion matrix is one of the most popular evaluation methods in tasks related to classification because it gives a comprehensive description of the prediction performance of the model. The table will show the comparison between the actual class labels and the predicted class labels that were produced by the model. The rows are the actual labels of the data set and the columns are the actual labels that were generated by the SVM classifier. Based on the visualization, it is possible to note that the model was able to classify a high number of patient records correctly. In particular, the model had accurately forecasted 22 cases of non-heart disease and 22 cases of heart disease patients. These are the correct classifications that are the true negatives and true positives of the model. Some misclassifications are also found in the confusion matrix. The model falsely diagnosed 10 patients who were not heart diseased and these will be termed as false positives.

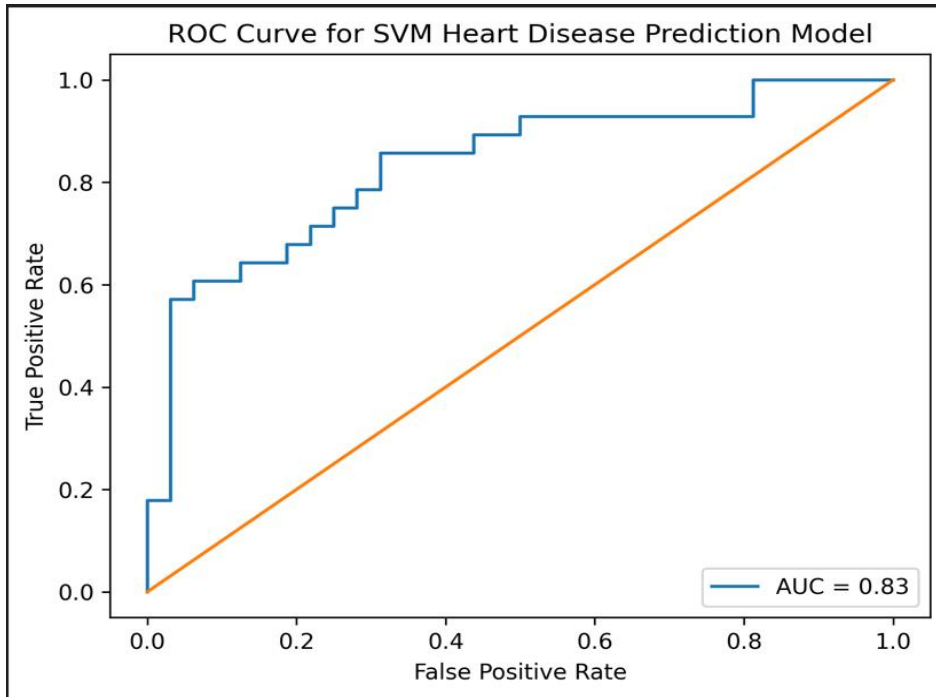

Figure 10: This image illustrates the performance of the SVM heart disease prediction model in terms of classification

Figure 10 shows the Receiver Operating Characteristic (ROC) curve of the Support Vector Machine model utilized in prediction of heart diseases. ROC curve is a significant assessment measure in a classification problem since it is used to determine the capability of the model to differentiate among various classes at different threshold values. The horizontal axis in the chart corresponds to False Positive Rate (FPR) and the vertical axis corresponds to True Positive Rate (or sensitivity). The straight line in the graph indicates the base level performance of a random classifier with predictions made by sheer chance. The model that outperforms random classification must give a curve which is above this diagonal line. As it is illustrated in the figure, the ROC curve of the SVM model shoots a lot higher than the baseline, which is a good indicator of a strong predictive performance. The value of the area under the curve (AUC) is about 0.83 which indicates that the model can well differentiate between heart disease and normal patients.

5. Future Improvements and Limitations

Although encouraging outcomes are achieved during this research, one should take into consideration multiple limitations when examining the results. The use of a relatively small dataset to train and evaluate the model is one of the limitations [48]. Despite the usefulness of the dataset in terms of clinical features, the dataset that is larger (with a larger number of different patient populations) can contribute to an even better model generalization and predictive accuracy. The other weakness is that the data used is not representative of actual medical records due to the fact that it only has a few clinical features [49]. The cardiovascular risk can be affected by other data including genetic data, imaging results, lifestyle and long-term medical

history in the context of practical healthcare settings. The ability of machine learning models to predict well may be improved with the added data sources. Another aspect that can be improved is model selection [50]. Although the Support Vector Machine algorithm has shown high performance in this research, other machine learning algorithms like random forests, gradient boosting, or deep learning models can give more information or add a better prediction value. The methodology of explainability might be extended in the future [51]. The explainable AI techniques like SHAP or LIME can also be advanced enough to give detailed explanations of a single prediction and based on this, clinicians can learn how certain attributes of a particular patient contribute to risk assessments [52].

6. Conclusion

In this study, an explainable artificial intelligence-based system, on how to assist clinical decision-making in precision healthcare systems via predicting heart disease via machine learning methods, was presented. The study made use of the Heart Disease Cleveland dataset that includes a variety of clinical characteristics of cardiovascular health such as age, cholesterol level, chest pain type, blood pressure, electrocardiographic findings, and maximum heart rate during physical activity. In a well-organized data preprocessing, exploratory data analysis, evaluation of relationship between features, significant data patterns and clinical indicators of heart disease were recognized. A predictive classification model based on Support Vector Machine (SVM) algorithm was used to create a model that would classify patients with and without heart disease by their clinical characteristics. The outcomes of the model analysis revealed the potentially good predictive accuracy of the model as shown by the analysis of the confusion matrix and Receiver Operating Characteristic (ROC) curve. The ROC analysis resulted in an area under the curve (AUC) value that was also high which implies that there is a high discrimination ability by the model implying that the model is capable of identifying cardiovascular risk in patients within the dataset. Besides predictive accuracy, the study also highlighted explainable artificial intelligence as significant to healthcare.

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