Stage 1: Study Replication

The performance metrics for each dataset and classifier developed by Doppala et al. are presented in the figure below (Doppala, Bhattacharyya, Janarthanan, & Baik, 2022).

TABLE 4: Achieved accuracies using benchmark classifiers.

Classification technique	Accuracy (%) achieved with the Cleveland dataset	Accuracy (%) achieved with the comprehensive dataset	Accuracy (%) achieved with the Mendeley dataset
Decision tree	77.86	82.56	95
Random forest	78.68	90.75	95.12
Naive Bayes	81.14	84.24	94.25
Logistic regression	81.96	84.03	95.25
Support vector machine	79.05	81.52	93.15
Gradient boosting	81.14	86.13	95.15
XGBoost	80.32	88.23	96.12

TABLE 5: Proposed model performance representation.

Classification technique	Accuracy (%) achieved with the Cleveland dataset	Accuracy (%) achieved with the comprehensive dataset	Accuracy (%) achieved with the Mendeley dataset
Proposed ensemble model	88.24	93.39	96.75

TABLE 6: Performance metrics of all the machine learning models.

Classification technique	Accuracy (%) achieved with the Cleveland dataset	Sensitivity	Specificity	Precision	Recall	$F1$-score	MCC
Decision tree	77.86	0.81	0.73	0.77	0.81	0.79	0.55
Random forest	78.68	0.78	0.77	0.80	0.78	0.79	0.55
Naive Bayes	81.14	0.87	0.73	0.79	0.87	0.83	0.62
Logistic regression	81.96	0.93	0.66	0.76	0.790.	0.84	0.63
Support vector machine	79.05	0.77	0.75	0.79	0.85	0.78	0.54
Gradient boosting	81.14	0.93	0.66	0.76	0.93	0.84	0.63
XGBoost	80.32	0.87	0.71	0.78	0.87	0.82	0.60
Proposed ensemble model	88.24	0.91	0.84	0.85	0.90	0.88	0.76
Classification technique	**Accuracy (%) achieved with the comprehensive dataset**	**Sensitivity**	**Specificity**	**Precision**	**Recall**	**$F1$-score**	**MCC**
Decision tree	82.56	0.79	0.85	0.83	0.79	0.81	0.65
Random forest	90.75	0.93	0.88	0.88	0.93	0.90	0.81
Naive Bayes	84.24	0.85	0.82	0.82	0.85	0.84	0.68
Logistic regression	84.03	0.87	0.80	0.81	0.87	0.84	0.68
Support vector machine	81.52	0.83	0.82	0.82	0.84	0.83	0.69
Gradient boosting	86.13	0.92	0.79	0.81	0.92	0.86	0.72
XGBoost	83.23	0.91	0.84	0.85	0.91	0.88	0.76
Proposed ensemble model	93.39	0.94	0.89	0.99	0.88	0.90	0.85
Classification technique	**Accuracy (%) achieved with the Mendeley dataset**	**Sensitivity**	**Specificity**	**Precision**	**Recall**	**$F1$-score**	**MCC**
Decision tree	95	0.95	0.94	0.96	0.95	0.95	0.88
Random forest	95.12	0.94	0.96	0.97	0.94	0.96	0.90
Naive Bayes	94.25	0.95	0.90	0.94	0.95	0.94	0.86
Logistic regression	95.25	0.97	0.95	0.97	0.97	0.97	0.92
Support vector machine	93.15	0.95	0.90	0.93	0.95	0.93	0.85
Gradient boosting	95.15	0.95	0.95	0.97	0.95	0.96	0.90
XGBoost	96.12	0.96	0.95	0.97	0.96	0.96	0.92
Proposed ensemble model	96.75	0.96	0.97	0.98	0.96	0.97	0.93

Bibliography

Doppala, B. P., Bhattacharyya, D., Janarthanan, M., & Baik, N. (2022, March 8). A Reliable Machine Intelligence Model for Accurate Identification of Cardiovascular Diseases Using Ensemble Techniques. Hindawi Journal of Healthcare Engineering, 2022. doi:https://doi.org/10.1155/2022/2585235

Dataset 2: Mendeley Dataset

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import pandas as pd
path = "/content/drive/MyDrive/CIND 820/Cardiovascular_Disease_Dataset.csv"
data_india = pd.read_csv(path,encoding='utf-8-sig')
data_india.head()
```

	patientid	age	gender	chestpain	restingBP	serumcholestrol	fastingbloodsugar	res
0	103368	53	1	2	171	0	0	
1	119250	40	1	0	94	229	0	
2	119372	49	1	2	133	142	0	
3	132514	43	1	0	138	295	1	
4	146211	31	1	1	199	0	0	

```
#Identify duplicate rows in Mendeley Data
india_rows = data_india.shape[0]
india_dups = data_india[data_india.duplicated(keep=False)].shape[0]
print('There are '+ str(india_dups)+ ' duplicate records out of '+ str(india_rows)+' total r

#Check for null values in Mendeley dataset
null_india =data_india.isna().sum().sum()
print("There are " + str(null_india) + " null values in the india dataset")
```

```
There are 0 duplicate records out of 1000 total records
There are 0 null values in the india dataset
```

```
#Drop patientid feature
data_india = data_india.drop('patientid', axis=1)
```

```
#one-hot coding of india Data categorical independent variables

#The variables treated with one-hot encoding is unclear in replication paper, however 5 vari
data_india_coded = pd.get_dummies(data_india, columns=['chestpain','restingrelectro','slope'


#Output new column names as list for ease of use in test train split below
data_india_coded.columns.values
```

```
array(['age', 'gender', 'restingBP', 'serumcholestrol',
       'fastingbloodsugar', 'maxheartrate', 'exerciseangia', 'oldpeak',
       'target', 'chestpain_1', 'chestpain_2', 'chestpain_3',
       'restingrelectro_1', 'restingrelectro_2', 'slope_1', 'slope_2',
       'slope_3', 'noofmajorvessels_1', 'noofmajorvessels_2',
       'noofmajorvessels_3'], dtype=object)
```

```
#Test Train Split

#Import applicable scikit-learn libraries
from sklearn.model_selection import train_test_split

#Divide data into independent variables and dependent variable
independent = data_india_coded.loc[:,['age', 'gender', 'restingBP', 'serumcholestrol','fasti
dependent = data_india_coded.loc[:,['target']]

#Use a 60:40 test split as in CMTH642 Lab 7 and Lab 10. Assign a random_state of 0 for repro
x_train, x_test, y_train, y_test = train_test_split(independent, dependent, random_state=0,


#Following advice of Jason Brownlee of https://machinelearningmastery.com/data-preparation-w
#Data Preparation for Machine Learning Data Cleaning, Feature Selection, and Data Transforms
#All data preparation must be fit on the training set only

#Data will be scaled using the MinMaxScaler
from sklearn.preprocessing import MinMaxScaler

#Subset of numerical features
india_numerical =['age', 'restingBP', 'serumcholestrol', 'maxheartrate', 'oldpeak']

#Initialize RobustScaler
scaler = MinMaxScaler()
#Fit on the training dataset to the RobustScaler instance. Fitting the data to the training
scaler.fit(x_train[india_numerical])

#Scale the training data using the RobustScaler instance
x_train[india_numerical] = scaler.transform(x_train[india_numerical])
#Scale the testing data using the RobustScaler instance
x_test[india_numerical] = scaler.transform(x_test[india_numerical])
```

```
#Decision Tree

from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier

#Initialize the decision tree classifier and assign to variable india_decision_tree. Assign
india_decision_tree = DecisionTreeClassifier(random_state=0)

#Fit the training data set to the decision tree model
india_decision_tree.fit(x_train, y_train.values.ravel()).predict(x_test)

#Predict the presence of heart disese by inputting the test data into the india_decision_tre
target_pred_decision_tree = india_decision_tree.predict(x_test)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score, matthew

accuracy_decision_tree =  round(accuracy_score(y_test, target_pred_decision_tree),4)*100
precision_decision_tree = round(precision_score(y_test, target_pred_decision_tree, pos_label
recall_decision_tree = round(recall_score(y_test, target_pred_decision_tree, pos_label=1),3)
f1_score_decision_tree = round(f1_score(y_test, target_pred_decision_tree, pos_label=1),3)
mcc_decision_tree = round(matthews_corrcoef(y_test, target_pred_decision_tree),3)
specificity_decision_tree = round(recall_score(y_test, target_pred_decision_tree, pos_label=

#Organize performance metrics into a list
performance_decision_tree = [["Decision Tree", accuracy_decision_tree, specificity_decision_

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_decision_tree, columns=['Model', 'Accuracy', '
performance_metrics.index = [""]
performance_metrics
```

	Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
	Decision Tree	92.75	0.933	0.944	0.923	0.934	0.854

```
#Random Forest

from sklearn.ensemble import RandomForestClassifier

#Initialize the random forest classifier and assign to variable india_decision_tree. Assign
india_random_forest = RandomForestClassifier(random_state=0)

#Fit the training data set to the random forest classifier
india_random_forest.fit(x_train, y_train.values.ravel()).predict(x_test)

#Predict the presence of heart disese by inputting the test data into the india_random_fores
target_pred_random_forest = india_random_forest.predict(x_test)

accuracy_random_forest =  round(accuracy_score(y_test, target_pred_random_forest),4)*100
precision_random_forest = round(precision_score(y_test, target_pred_random_forest, pos_label
recall_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=1),3)
f1_score_random_forest = round(f1_score(y_test, target_pred_random_forest, pos_label=1),3)
mcc_random_forest = round(matthews_corrcoef(y_test, target_pred_random_forest),3)
specificity_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=

#Organize performance metrics into a list
performance_random_forest = [["Random Forest", accuracy_random_forest,specificity_random_for

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_random_forest, columns=['Model', 'Accuracy', '
performance_metrics.index = [""]
performance_metrics
```

	Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
	Random Forest	96.0	0.944	0.956	0.973	0.964	0.919

```
#Naive Bayes

#The application of Naive Bayes in the paper is unclear. The dataset contains both categoric
#Here we will applying different Naive Bayes classifiers to the categorical and numerical fe
from sklearn.naive_bayes import  CategoricalNB, GaussianNB

#Initialize the naive bayes models and assign to variable
india_naive_numerical = GaussianNB()
india_naive_categorical = CategoricalNB()

#List categorical and numerical feature names
india_categorical_nb = ['gender', 'fastingbloodsugar','exerciseangia','chestpain_1', 'chestp
india_numerical_nb = ['age', 'restingBP',   'serumcholestrol', 'maxheartrate','oldpeak']

# Fit the categorical features in the training data set to the categorical naive bayes model
india_naive_categorical.fit(x_train[india_categorical_nb], y_train.values.ravel())

#Fit the numerical features in the training data set to the gaussian naive bayes model
india_naive_numerical.fit(x_train[india_numerical_nb], y_train.values.ravel())

# Predict probabilities for using categorical and numerical features
probability_categorical = india_naive_categorical.predict_proba(x_test[india_categorical_nb]
probability_numerical= india_naive_numerical.predict_proba(x_test[india_numerical_nb])

#Combine the probabilities using the product rule
total_probability = probability_categorical * probability_numerical

#We can use this code to select the class that has the greatest probability for a given row
import numpy as np
target_pred_naive = np.argmax(total_probability, axis=1)

#Calculate performance metrics
accuracy_naive =  round(accuracy_score(y_test, target_pred_naive),4)*100
precision_naive = round(precision_score(y_test, target_pred_naive, pos_label=1),3)
recall_naive = round(recall_score(y_test, target_pred_naive, pos_label=1),3)
f1_score_naive = round(f1_score(y_test, target_pred_naive, pos_label=1),3)
mcc_naive = round(matthews_corrcoef(y_test, target_pred_naive),3)
specificity_naive = round(recall_score(y_test, target_pred_naive, pos_label=0),3)

#Organize performance metrics into a list
performance_naive = [["Naive Bayes", accuracy_naive,specificity_naive,precision_naive,recall

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_naive, columns=['Model', 'Accuracy', 'Specific
performance_metrics.index = [""]
performance_metrics
```

	Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
	Naive Bayes	94.0	0.911	0.93	0.964	0.947	0.879

```
#Logistic Regression

#Import logistic regression model from scikit-learn libraries
from sklearn.linear_model import LogisticRegression

#Initialize the logistic regression model and assign to variable india_logistic_reg variable
india_logistic_reg = LogisticRegression(random_state=0, max_iter=1000000)

#Fit the training data set to the logistic model
india_logistic_reg.fit(x_train, y_train.values.ravel())

#Predict the presence of heart disese by inputting the test data into the india_logistic_reg
target_pred_logistic = india_logistic_reg.predict(x_test)

accuracy_logistic =  round(accuracy_score(y_test, target_pred_logistic),4)*100
precision_logistic = round(precision_score(y_test, target_pred_logistic, pos_label=1),3)
recall_logistic = round(recall_score(y_test, target_pred_logistic, pos_label=1),3)
f1_score_logistic = round(f1_score(y_test, target_pred_logistic, pos_label=1),3)
mcc_logistic = round(matthews_corrcoef(y_test, target_pred_logistic),3)
specificity_logistic = round(recall_score(y_test, target_pred_logistic, pos_label=0),3)

#Organize performance metrics into a list
performance_logistic = [["Logistic Regression", accuracy_logistic,specificity_logistic,preci

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_logistic, columns=['Model', 'Accuracy', 'Speci
performance_metrics.index = [""]
performance_metrics
```

	Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
	Logistic Regression	96.0	0.939	0.952	0.977	0.964	0.919

```
#Import support vector machine from scikit-learn libraries
from sklearn import svm

#Initialize the support vector machine classifier and assign to variable india_decision_tree
india_support_vector = svm.SVC(kernel='linear', random_state=0)

#Fit the training data set to the support vector machine classifier
india_support_vector.fit(x_train, y_train.values.ravel()).predict(x_test)

#Predict the presence of heart disese by inputting the test data into the india_support_vect
target_pred_support_vector = india_support_vector.predict(x_test)

accuracy_support_vector =  round(accuracy_score(y_test, target_pred_support_vector),4)*100
precision_support_vector = round(precision_score(y_test, target_pred_support_vector, pos_lab
recall_support_vector = round(recall_score(y_test, target_pred_support_vector, pos_label=1),
f1_score_support_vector = round(f1_score(y_test, target_pred_support_vector, pos_label=1),3)
mcc_support_vector = round(matthews_corrcoef(y_test, target_pred_support_vector),3)
specificity_support_vector = round(recall_score(y_test, target_pred_support_vector, pos_labe

#Organize performance metrics into a list
performance_support_vector = [["Support Vector", accuracy_support_vector,specificity_support

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_support_vector, columns=['Model', 'Accuracy',
performance_metrics.index = [""]
performance_metrics
```

	Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
	Support Vector	96.75	0.955	0.964	0.977	0.971	0.934

```
#Gradient Boosting

#Import gradient boosting classifier from scikit-learn libraries
from sklearn.ensemble import GradientBoostingClassifier

#Initialize the support vector machine classifier and assign to variable india_decision_tree
india_gradient = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0, max_depth=1

#Fit the training data set to the support vector machine classifier
india_gradient.fit(x_train, y_train.values.ravel()).predict(x_test)

#Predict the presence of heart disese by inputting the test data into the india_gradient
target_pred_gradient = india_gradient.predict(x_test)

accuracy_gradient =  round(accuracy_score(y_test, target_pred_gradient),4)*100
precision_gradient = round(precision_score(y_test, target_pred_gradient, pos_label=1),3)
recall_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=1),3)
f1_score_gradient = round(f1_score(y_test, target_pred_gradient, pos_label=1),3)
mcc_gradient = round(matthews_corrcoef(y_test, target_pred_gradient),3)
specificity_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=0),3)

#Organize performance metrics into a list
performance_gradient = [["Gradient Boosting", accuracy_gradient,specificity_gradient,precisi

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_gradient, columns=['Model', 'Accuracy','Specif
performance_metrics.index = [""]
performance_metrics
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
Gradient Boosting	97.5	0.95	0.961	0.995	0.978	0.95

```
#XGBoost

#Import xgboost
import xgboost as xgb

#Initialize the support vector machine classifier and assign to variable india_decision_tree
india_xgb = xgb.XGBClassifier(n_estimators=100, objective='binary:logistic', tree_method='hi

#Fit the training data set to the support vector machine classifier
india_xgb.fit(x_train, y_train.values.ravel()).predict(x_test)

#Predict the presence of heart disese by inputting the test data into the india_xgb
target_pred_xgb = india_xgb.predict(x_test)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score

accuracy_xgb =  round(accuracy_score(y_test, target_pred_xgb),4)*100
precision_xgb = round(precision_score(y_test, target_pred_xgb, pos_label=1),3)
recall_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=1),3)
f1_score_xgb = round(f1_score(y_test, target_pred_xgb, pos_label=1),3)
mcc_xgb = round(matthews_corrcoef(y_test, target_pred_xgb),3)
specificity_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=0),3)

#Organize performance metrics into a list
performance_xgb = [["XGBoost", accuracy_xgb,specificity_xgb,precision_xgb,recall_xgb,f1_scor

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_xgb, columns=['Model', 'Accuracy','Specificity
performance_metrics.index = [""]
performance_metrics
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
XGBoost	97.5	0.966	0.973	0.982	0.977	0.949

```
#Ensemble Model

#Import VotingClassifier to combine model predictions
from sklearn.ensemble import VotingClassifier

#Initialize a categorical naive bayes classifier and train using categorical training set
ensemble_categorical_nb = CategoricalNB()
ensemble_categorical_nb.fit(x_train[india_categorical_nb], y_train.values.ravel())

#Initialize a gaussian naive bayes classifier and train using numerical (i.e continuous nume
ensemble_numerical_nb = GaussianNB()
ensemble_numerical_nb.fit(x_train[india_numerical_nb], y_train.values.ravel())

# Initialize remaining classifier types and fit the entire training setata
ensemble_random_forest = RandomForestClassifier()
ensemble_random_forest.fit(x_train, y_train.values.ravel())

ensemble_svm = svm.SVC(probability=True)
ensemble_svm.fit(x_train, y_train.values.ravel())

ensemble_gradient = GradientBoostingClassifier()
ensemble_gradient.fit(x_train, y_train.values.ravel())

#Specify Algorithms and initialize ensemble model using a soft voting classifier
algorithms = [('ensemble_categorical_nb',ensemble_categorical_nb),('ensemble_numerical_nb',e
ensemble = VotingClassifier(estimators=algorithms, voting='soft')

#Now we can fit each model to voting classifier instance, selecting the categorical variable
ensemble.fit(
    np.column_stack([ensemble_categorical_nb.predict_proba(x_train[india_categorical_nb]),
                     ensemble_numerical_nb.predict_proba(x_train[india_numerical_nb]),
                     ensemble_random_forest.predict_proba(x_train),
                     ensemble_gradient.predict_proba(x_train),
                     ensemble_svm.predict_proba(x_train)]),
    y_train.values.ravel()
)

#With the ensemble model, we can make predictions on the target values
target_pred_ensemble = ensemble.predict(
    np.column_stack([ensemble_categorical_nb.predict_proba(x_test[india_categorical_nb]),
                     ensemble_numerical_nb.predict_proba(x_test[india_numerical_nb]),
                     ensemble_random_forest.predict_proba(x_test),
                     ensemble_gradient.predict_proba(x_test),
                     ensemble_svm.predict_proba(x_test)])
)

accuracy_ensemble =  round(accuracy_score(y_test, target_pred_ensemble),4)*100
precision_ensemble = round(precision_score(y_test, target_pred_ensemble, pos_label=1),3)
recall_ensemble = round(recall_score(y_test, target_pred_ensemble, pos_label=1),3)
f1_score_ensemble = round(f1_score(y_test, target_pred_ensemble, pos_label=1),3)
mcc_ensemble = round(matthews_corrcoef(y_test, target_pred_ensemble),3)
```

```
specificity_ensemble = round(recall_score(y_test, target_pred_ensemble, pos_label=0),3)

#Organize performance metrics into a list
performance_ensemble = [["Ensemble", accuracy_ensemble,specificity_ensemble,precision_ensemb

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_ensemble, columns=['Model', 'Accuracy','Specif
performance_metrics.index = [""]
performance_metrics
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
Ensemble	97.5	0.966	0.973	0.982	0.977	0.949

Stage 1A: Changes to Approximate Study Accuracy

Hyperparameter tuning will be attempted to approximate the accuracy measure of the study paper.

```
#Import GridSearchCV class from sklearn library for hyperparameter tuning
from sklearn.model_selection import GridSearchCV

#Initialize the decision tree classifier
india_decision_tree = DecisionTreeClassifier(random_state=42)

#A parameter grid was created using the defaults and selected integers
param_grid = {'criterion': ['gini', 'entropy'],
              'max_depth': [None, 1,2,10, 20, 30],
              'min_samples_split': [2, 5, 10,15,18],
              'min_samples_leaf': [1, 2, 4]}

#Initialize the GridSearchCV class using the decision model, the parameter grid and a 10-fol
grid_india_dt = GridSearchCV(india_decision_tree , param_grid, cv=10)
grid_india_dt.fit(x_train, y_train)

#Output the best parameters, the model is optimized based on accuracy score
best_params_dt = grid_india_dt.best_params_
print(best_params_dt)

#Fit the model using athe best parameters
india_decision_tree = DecisionTreeClassifier(**best_params_dt, random_state=42)
india_decision_tree.fit(x_train, y_train)

# Use the best model for predictions and recalculate metrics
target_pred_decision_tree = india_decision_tree.predict(x_test)

#Calculate Performance Metrics
accuracy_decision_tree =  round(accuracy_score(y_test, target_pred_decision_tree),4)*100
precision_decision_tree = round(precision_score(y_test, target_pred_decision_tree, pos_label
recall_decision_tree = round(recall_score(y_test, target_pred_decision_tree, pos_label=1), 3
f1_score_decision_tree = round(f1_score(y_test, target_pred_decision_tree, pos_label=1), 3)
mcc_decision_tree = round(matthews_corrcoef(y_test, target_pred_decision_tree), 3)
specificity_decision_tree = round(recall_score(y_test, target_pred_decision_tree, pos_label=

# Organize performance metrics into a list
performance_decision_tree = [["Decision Tree", accuracy_decision_tree, specificity_decision_

# Create a DataFrame of performance metrics
grid_dt_pm = pd.DataFrame(performance_decision_tree, columns=['Model', 'Accuracy', 'Specific
grid_dt_pm.index = [""]

grid_dt_pm

#There are improvements to the metrics with the exception of specificity
```

```
{'criterion': 'entropy', 'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split':
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
Decision Tree	97.0	0.972	0.977	0.968	0.973	0.939

```
#Import GridSearchCV class from sklearn library for hyperparameter tuning
from sklearn.model_selection import GridSearchCV

#Initialize the random forest classifier and assign to variable india_random_forest. Assign
india_random_forest = RandomForestClassifier(random_state=42)

#A parameter grid was created using the defaults and selected integers to cycle through in c
#These features were selected based on the values available in the sklearn documentation
param_dist = {'n_estimators': [50, 100, 200, 300],
              'max_features': ['auto', 'sqrt', 'log2'],
              'max_depth': [None, 1,2,10,20,30],
              'min_samples_split': [2,3,4,5,10,15,18,20],
              'min_samples_leaf': [1,2,4,5,6]}

#Initialize the GridSearchCV class using the random forest, the parameter grid and a 10-folc
grid_india_rf = GridSearchCV(india_random_forest , param_grid, cv=10)
grid_india_rf.fit(x_train, y_train.values.ravel())

#Output the best parameters, the model is optimized based on accuracy score
best_params_rf = grid_india_rf.best_params_
print(best_params_rf)

#Fit the model using athe best parameters
india_random_forest = RandomForestClassifier(**best_params_dt, random_state=42)
india_random_forest.fit(x_train, y_train.values.ravel())

# Use the best model for predictions and recalculate metrics
target_pred_random_forest = india_random_forest.predict(x_test)

#Calculate Performance Metrics
accuracy_random_forest =  round(accuracy_score(y_test, target_pred_random_forest),4)*100
precision_random_forest = round(precision_score(y_test, target_pred_random_forest, pos_label
recall_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=1),3)
f1_score_random_forest = round(f1_score(y_test, target_pred_random_forest, pos_label=1),3)
mcc_random_forest = round(matthews_corrcoef(y_test, target_pred_random_forest),3)
specificity_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=

# Organize performance metrics into a list
performance_decision_tree = [["Random Forest", accuracy_random_forest, specificity_random_fo

# Create a DataFrame of performance metrics
grid_rf_pm = pd.DataFrame(performance_random_forest, columns=['Model', 'Accuracy', 'Specific
grid_rf_pm.index = [""]

grid_rf_pm

#Despite performing GridSearchCV, the accuracy remains unchanged. RandomSearchCV is attempte
```

```
{'criterion': 'entropy', 'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 2}
        Model  Accuracy  Specificity  Precision  Recall  F1 Score   MCC
```

```
#Import RandomizedSearchCV class from sklearn library for hyperparameter tuning
from sklearn.model_selection import RandomizedSearchCV

#Initialize the random forest classifier and assign to variable india_random_forest. Assign
india_random_forest = RandomForestClassifier(random_state=42)

#A parameter grid was created using the defaults and selected integers to cycle through in c
#These features were selected based on the values available in the sklearn documentation
param_dist = {'n_estimators': [50, 100, 200, 300],
              'max_features': ['auto', 'sqrt', 'log2'],
              'max_depth': [None, 1,2,10,20,30],
              'min_samples_split': [2,3,4,5,10,15,18,20],
              'min_samples_leaf': [1,2,4,5,6]}

#Initialize the RandomizedSearchCV class using the decision model, the parameter grid and a
grid_india_rf = RandomizedSearchCV(india_random_forest , param_grid, cv=10)
grid_india_rf.fit(x_train, y_train.values.ravel())

#Output the best parameters, the model is optimized based on accuracy score
best_params_rf = grid_india_rf.best_params_
print(best_params_rf)

#Fit the model using athe best parameters
india_random_forest = RandomForestClassifier(**best_params_dt, random_state=42)
india_random_forest.fit(x_train, y_train.values.ravel())

# Use the best model for predictions and recalculate metrics
target_pred_random_forest = india_random_forest.predict(x_test)

#Calculate Performance Metrics
accuracy_random_forest =  round(accuracy_score(y_test, target_pred_random_forest),4)*100
precision_random_forest = round(precision_score(y_test, target_pred_random_forest, pos_label
recall_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=1),3)
f1_score_random_forest = round(f1_score(y_test, target_pred_random_forest, pos_label=1),3)
mcc_random_forest = round(matthews_corrcoef(y_test, target_pred_random_forest),3)
specificity_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=

# Organize performance metrics into a list
performance_decision_tree = [["Random Forest", accuracy_random_forest, specificity_random_fo

# Create a DataFrame of performance metrics
grid_rf_pm = pd.DataFrame(performance_random_forest, columns=['Model', 'Accuracy', 'Specific
grid_rf_pm.index = [""]

grid_rf_pm

#Results are the same despite performing RandomSearchCV
```

```
{'min_samples_split': 5, 'min_samples_leaf': 1, 'max_depth': 30, 'criterion': 'gini'}
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
Random Forest	96.0	0.944	0.956	0.973	0.964	0.919

```
#Gradient Boosting

#Initialize the gradient boosting classifier and assign to variable india_gradient. Assign r
india_gradient = GradientBoostingClassifier(random_state=42)

#A parameter grid was created using selected integers to cycle through in order to optimize
#These features were selected based on the values available in the sklearn documentation
param_dist = {'n_estimators': [50, 100, 200],
              'learning_rate': [0.01, 0.1, 0.2],
              'max_depth': [3, 4, 5],
              'min_samples_split': [2, 5, 10],
              'min_samples_leaf': [1, 2, 4]}

#Fit the training data set to the support vector machine classifier
india_gradient.fit(x_train, y_train.values.ravel()).predict(x_test)

#Initialize the GridSearchCV class using the gradient boosting, the parameter grid and a 10-
grid_india_gb = GridSearchCV(india_gradient, param_dist, cv=10)
grid_india_gb.fit(x_train, y_train.values.ravel())

#Output the best parameters, the model is optimized based on accuracy score
best_params_gb = grid_india_gb.best_params_
print(best_params_gb)

#Fit the model using athe best parameters
india_gradient= GradientBoostingClassifier(**best_params_gb, random_state=42)
india_gradient.fit(x_train, y_train.values.ravel())

#Predict the presence of heart disese by inputting the test data into the india_gradient
target_pred_gradient = india_gradient.predict(x_test)

accuracy_gradient =  round(accuracy_score(y_test, target_pred_gradient),4)*100
precision_gradient = round(precision_score(y_test, target_pred_gradient, pos_label=1),3)
recall_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=1),3)
f1_score_gradient = round(f1_score(y_test, target_pred_gradient, pos_label=1),3)
mcc_gradient = round(matthews_corrcoef(y_test, target_pred_gradient),3)
specificity_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=0),3)

#Organize performance metrics into a list
performance_gradient = [["Gradient Boosting", accuracy_gradient,specificity_gradient,precisi

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_gradient, columns=['Model', 'Accuracy','Specif
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_gradient = performance_metrics

performance_metrics
```

```
{'learning_rate': 0.1, 'max_depth': 3, 'min_samples_leaf': 2, 'min_samples_split': 10, '
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
Gradient Boosting	97.5	0.966	0.973	0.982	0.977	0.949

```
#XGBoost

#Initialize the support vector machine classifier and assign to variable india_decision_tree
india_xgb = xgb.XGBClassifier(enable_categorical=True, seed= 42)

#A parameter grid was created using the defaults and selected integers to cycle through in c
#These features were selected based on the values available in the sklearn documentation
param_grid = {
    'n_estimators': [50, 100, 200],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 4, 5],
    'subsample': [0.8, 0.9, 1.0],
    'colsample_bytree': [0.8, 0.9, 1.0]
}

#Initialize the RandomizedSearchCV class using the decision model, the parameter grid and a
grid_india_xgb = GridSearchCV(india_xgb , param_grid, cv=10)
grid_india_xgb.fit(x_train, y_train.values.ravel())

#Output the best parameters, the model is optimized based on accuracy score
best_params_xgb = grid_india_xgb.best_params_
print(best_params_xgb)

#Fit the model using athe best parameters
india_xgb = xgb.XGBClassifier(**best_params_xgb, seed=42)
india_xgb.fit(x_train, y_train.values.ravel())

# Use the best model for predictions and recalculate metrics
target_pred_random_forest = india_xgb.predict(x_test)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score

accuracy_xgb =  round(accuracy_score(y_test, target_pred_xgb),4)*100
precision_xgb = round(precision_score(y_test, target_pred_xgb, pos_label=1),3)
recall_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=1),3)
f1_score_xgb = round(f1_score(y_test, target_pred_xgb, pos_label=1),3)
mcc_xgb = round(matthews_corrcoef(y_test, target_pred_xgb),3)
specificity_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=0),3)

#Organize performance metrics into a list
performance_xgb = [["XGBoost", accuracy_xgb,specificity_xgb,precision_xgb,recall_xgb,f1_scor

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_xgb, columns=['Model', 'Accuracy','Specificity
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_xgb= performance_metrics

performance_metrics
```

```
{'colsample_bytree': 0.8, 'learning_rate': 0.1, 'max_depth': 4, 'n_estimators': 100, 'su
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
XGBoost	97.5	0.966	0.973	0.982	0.977	0.949

Stage 2: Improvements to Classifiers

```
import pandas as pd
path = "/content/drive/MyDrive/CIND 820/Cardiovascular_Disease_Dataset.csv"
data_india = pd.read_csv(path,encoding='utf-8-sig')
data_india.head()
```

	patientid	age	gender	chestpain	restingBP	serumcholestrol	fastingbloodsugar	res
0	103368	53	1	2	171	0	0	
1	119250	40	1	0	94	229	0	
2	119372	49	1	2	133	142	0	
3	132514	43	1	0	138	295	1	
4	146211	31	1	1	199	0	0	

```
#Identify duplicate rows in Mendeley Data
india_rows = data_india.shape[0]
india_dups = data_india[data_india.duplicated(keep=False)].shape[0]
print('There are '+ str(india_dups)+ ' duplicate records out of '+ str(india_rows)+' total r

#Check for null values in Mendeley dataset
null_india =data_india.isna().sum().sum()
print("There are " + str(null_india) + " null values in the india dataset")
```

```
There are 0 duplicate records out of 1000 total records
There are 0 null values in the india dataset
```

```
#Drop patientid feature
data_india = data_india.drop('patientid', axis=1)
```

```
#one-hot coding of india Data categorical independent variables

#The variables treated with one-hot encoding is unclear in replication paper, however 5 vari
data_india_coded = pd.get_dummies(data_india, columns=['chestpain','restingrelectro','slope'
```

```
#Output new column names as list for ease of use in test train split below
data_india_coded.columns.values
```

```
array(['age', 'gender', 'restingBP', 'serumcholestrol',
       'fastingbloodsugar', 'maxheartrate', 'exerciseangia', 'oldpeak',
       'target', 'chestpain_1', 'chestpain_2', 'chestpain_3',
       'restingrelectro_1', 'restingrelectro_2', 'slope_1', 'slope_2',
       'slope_3', 'noofmajorvessels_1', 'noofmajorvessels_2',
       'noofmajorvessels_3'], dtype=object)
```

```
#Test Train Split

#Import applicable scikit-learn libraries
from sklearn.model_selection import train_test_split

#Divide data into independent variables and dependent variable
independent = data_india_coded.loc[:,['age', 'gender', 'restingBP', 'serumcholestrol','fasti
dependent = data_india_coded.loc[:,['target']]

#Use a 60:40 test split as in CMTH642 Lab 7 and Lab 10. Assign a random_state of 0 for repro
x_train, x_test, y_train, y_test = train_test_split(independent, dependent, random_state=0,


#Following advice of Jason Brownlee of https://machinelearningmastery.com/data-preparation-w
#Data Preparation for Machine Learning Data Cleaning, Feature Selection, and Data Transforms
#All data preparation must be fit on the training set only

#Data will be scaled using the robust scaler that is less susceptible to outliers
from sklearn.preprocessing import RobustScaler

#Subset of numerical features
india_numerical =['age', 'restingBP', 'serumcholestrol', 'maxheartrate', 'oldpeak']

#Initialize RobustScaler
scaler = RobustScaler()
#Fit on the training dataset to the RobustScaler instance. Fitting the data to the training
scaler.fit(x_train[india_numerical])

#Scale the training data using the RobustScaler instance
x_train[india_numerical] = scaler.transform(x_train[india_numerical])
#Scale the testing data using the RobustScaler instance
x_test[india_numerical] = scaler.transform(x_test[india_numerical])
```

```
#Feature Selection: Numerical Features - Binary Output

#Import Statistics module
from scipy.stats import ttest_ind

#Merge the dataframes to assist in separation of the healthy and diseased instances
india_merge = x_train.join(y_train)

#Separate training set into diseased and healthy dataframes
disease = india_merge[india_merge['target'] == 1]
healthy = india_merge[india_merge['target']==0]

#Separate age features into diseased and healthy dataframes
age_disease = disease['age']
age_healthy = healthy['age']

t_statistic, p_value = ttest_ind(age_disease, age_healthy)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [["age", t_statistic,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'T-Statistic','P-Value', 'Acc
simple_results.index = [""]

simple_results
```

	Feature	T-Statistic	P-Value	Accept?
	age	0.049672	0.9604	N

```
#Feature Selection: Numerical Features - Binary Output

#Import Statistics module
from scipy.stats import ttest_ind

#Merge the dataframes to assist in separation of the healthy and diseased instances
india_merge = x_train.join(y_train)

#Separate training set into diseased and healthy dataframes
disease = india_merge[india_merge['target'] == 1]
healthy = india_merge[india_merge['target']==0]

#Separate age features into diseased and healthy dataframes
age_disease = disease['restingBP']
age_healthy = healthy['restingBP']

t_statistic, p_value = ttest_ind(age_disease, age_healthy)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [['restingBP', t_statistic,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'T-Statistic','P-Value', 'Acc
simple_results.index = [""]

simple_results
```

Feature	T-Statistic	P-Value	Accept?
restingBP	13.933704	2.028086e-38	Y

```
#Feature Selection: Numerical Features - Binary Output

#Import Statistics module
from scipy.stats import ttest_ind

#Merge the dataframes to assist in separation of the healthy and diseased instances
india_merge = x_train.join(y_train)

#Separate training set into diseased and healthy dataframes
disease = india_merge[india_merge['target'] == 1]
healthy = india_merge[india_merge['target']==0]

#Separate age features into diseased and healthy dataframes
age_disease = disease['serumcholestrol']
age_healthy = healthy['serumcholestrol']

t_statistic, p_value = ttest_ind(age_disease, age_healthy)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [['serumcholestrol', t_statistic,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'T-Statistic','P-Value', 'Acc
simple_results.index = [""]

simple_results
```

	Feature	T-Statistic	P-Value	Accept?
	serumcholestrol	4.198321	0.000031	Y

```
#Feature Selection: Numerical Features - Binary Output

#Import Statistics module
from scipy.stats import ttest_ind

#Merge the dataframes to assist in separation of the healthy and diseased instances
india_merge = x_train.join(y_train)

#Separate training set into diseased and healthy dataframes
disease = india_merge[india_merge['target'] == 1]
healthy = india_merge[india_merge['target']==0]

#Separate age features into diseased and healthy dataframes
age_disease = disease['maxheartrate']
age_healthy = healthy['maxheartrate']

t_statistic, p_value = ttest_ind(age_disease, age_healthy)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [['maxheartrate', t_statistic,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'T-Statistic','P-Value', 'Acc
simple_results.index = [""]

simple_results
```

	Feature	T-Statistic	P-Value	Accept?
	maxheartrate	4.932895	0.000001	Y

```
#Feature Selection: Numerical Features - Binary Output

#Import Statistics module
from scipy.stats import ttest_ind

#Merge the dataframes to assist in separation of the healthy and diseased instances
india_merge = x_train.join(y_train)

#Separate training set into diseased and healthy dataframes
disease = india_merge[india_merge['target'] == 1]
healthy = india_merge[india_merge['target']==0]

#Separate age features into diseased and healthy dataframes
age_disease = disease['oldpeak']
age_healthy = healthy['oldpeak']

t_statistic, p_value = ttest_ind(age_disease, age_healthy)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [['oldpeak', t_statistic,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'T-Statistic','P-Value', 'Acc
simple_results.index = [""]

simple_results
```

Feature	T-Statistic	P-Value	Accept?
oldpeak	2.338092	0.019711	Y

```
#Calculating odds ratios for categorical features with only 2 levels (i.e. binary features)

import pandas as pd
#Import fisher exact to perform odds ratio test
from scipy.stats import fisher_exact

#Construct a contingency table
india_sex = pd.crosstab(x_train['gender'], y_train['target'])

# Calculate odds ratio and p-value for india sex feature
odds_ratio, p_value = fisher_exact(india_sex)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [['gender', odds_ratio,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'Odds Ratio','P-Value', 'Acce
simple_results.index = [""]

simple_results
```

Feature	Odds Ratio	P-Value	Accept?
gender	1.048047	0.8418	N

```
#Calculating odds ratios for categorical features with only 2 levels (i.e. binary features)

import pandas as pd
#Import fisher exact to perform odds ratio test
from scipy.stats import fisher_exact

#Construct a contingency table
india_fbs = pd.crosstab(x_train['fastingbloodsugar'], y_train['target'])

# Calculate odds ratio and p-value for india fasting blood sugar feature
odds_ratio, p_value = fisher_exact(india_fbs)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [['fastingbloodsugar', odds_ratio,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'Odds Ratio','P-Value', 'Acce
simple_results.index = [""]

simple_results
```

	Feature	Odds Ratio	P-Value	Accept?
	fastingbloodsugar	4.229369	2.109827e-13	Y

```
#Calculating odds ratios for categorical features with only 2 levels (i.e. binary features)

import pandas as pd
#Import fisher exact to perform odds ratio test
from scipy.stats import fisher_exact

#Construct a contingency table
india_exang = pd.crosstab(x_train['exerciseangia'], y_train['target'])

# Calculate odds ratio and p-value for india fasting blood sugar feature
odds_ratio, p_value = fisher_exact(india_exang)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [['exerciseangia', odds_ratio,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'Odds Ratio','P-Value', 'Acce
simple_results.index = [""]

simple_results
```

Feature	Odds Ratio	P-Value	Accept?
exerciseangia	0.872977	0.453631	N

```
#Calculating chi-squared test for categorical features with more than 2 levels

#Import necessary classes
from scipy.stats import chi2_contingency
from scipy.stats import chi2

#Filter uncoded, raw data table to reflect rows from training set
india_chi = data_india.loc[x_train.index, :]

#Crosstabulate data in filtered, uncoded, raw data table
india_cp = pd.crosstab(india_chi['chestpain'], india_chi['target'])

# Calculate chi_sq value and p-value for india chest pain feature
chi_sq, p_value, dof, expected = chi2_contingency(india_cp)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [['chestpain', chi_sq,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'Chi-Squared','P-Value', 'Acc
simple_results.index = [""]

simple_results
```

Feature	Chi-Squared	P-Value	Accept?
chestpain	190.11964	5.751285e-41	Y

```
#Calculating chi-squared test for categorical features with more than 2 levels

#Import necessary classes
from scipy.stats import chi2_contingency
from scipy.stats import chi2

#Filter uncoded, raw data table to reflect rows from training set
india_chi = data_india.loc[x_train.index, :]

#Crosstabulate data in filtered, uncoded, raw data table
india_cp = pd.crosstab(india_chi['restingrelectro'], india_chi['target'])

# Calculate chi_sq value and p-value for india restecg feature
chi_sq, p_value, dof, expected = chi2_contingency(india_cp)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [['restingelectro', chi_sq,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'Chi-Squared','P-Value', 'Acc
simple_results.index = [""]

simple_results
```

	Feature	Chi-Squared	P-Value	Accept?
	restingelectro	100.532527	1.477880e-22	Y

```
#Calculating chi-squared test for categorical features with more than 2 levels

#Import necessary classes
from scipy.stats import chi2_contingency
from scipy.stats import chi2

#Filter uncoded, raw data table to reflect rows from training set
india_chi = data_india.loc[x_train.index, :]

#Crosstabulate data in filtered, uncoded, raw data table
india_cp = pd.crosstab(india_chi['slope'], india_chi['target'])

# Calculate chi_sq value and p-value for india restecg feature
chi_sq, p_value, dof, expected = chi2_contingency(india_cp)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [['slope', chi_sq,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'Chi-Squared','P-Value', 'Acc
simple_results.index = [""]

simple_results
```

Feature	Chi-Squared	P-Value	Accept?
slope	441.466344	2.302346e-95	Y

```
#Calculating chi-squared test for categorical features with more than 2 levels

#Import necessary classes
from scipy.stats import chi2_contingency
from scipy.stats import chi2

#Filter uncoded, raw data table to reflect rows from training set
india_chi = data_india.loc[x_train.index, :]

#Crosstabulate data in filtered, uncoded, raw data table
india_cp = pd.crosstab(india_chi['noofmajorvessels'], india_chi['target'])

# Calculate chi_sq value and p-value for india restecg feature
chi_sq, p_value, dof, expected = chi2_contingency(india_cp)

#Test p-value
if p_value < 0.05:
    test = "Y"
else:
    test = "N"

#Organize performance metrics into a list
results_list = [['noofmajorvessels', chi_sq,p_value,test]]

#Create dataframe of performance metrics
simple_results= pd.DataFrame(results_list, columns=['Feature', 'Chi-Squared','P-Value', 'Acc
simple_results.index = [""]

simple_results
```

	Feature	Chi-Squared	P-Value	Accept?
	noofmajorvessels	182.503197	2.540212e-39	Y

```
#Modify training and test records

#Features to drop based on simple filters
features_remove = ['age','gender','exerciseangia']

#Remove selected features from x_train and x_test to evaluate model based on hold-out methoc
x_train_simple = x_train.drop(columns=features_remove)
x_test_simple = x_test.drop(columns=features_remove)
```

```
#Modify consistent dataset for k-fold cross-validation

#Features to drop based on simple filters
features_remove = ['age','gender','exerciseangia']

#Data will be scaled using the robust scaler that is less susceptible to outliers
from sklearn.preprocessing import RobustScaler

#Subset of numerical features
india_numerical =['restingBP', 'serumcholestrol', 'maxheartrate', 'oldpeak']

#Initialize RobustScaler
scaler = RobustScaler()

#Separate target column
x_simple = data_india_coded.drop(columns=['target'] + features_remove)
y_simple = data_india_coded['target']

#Fit the consistent dataset to the RobustScaler instance.
x_simple[india_numerical] = scaler.fit_transform(x_simple[india_numerical])
```

```
#Decision Tree

from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier

#Import classes to calculate memory consumption and runtime
import timeit
import psutil

#Initialize the decision tree classifier and assign to variable india_decision_tree. Assign
india_decision_tree = DecisionTreeClassifier(random_state=42)

#Begin timing of fitting and prediction process
start_time = timeit.default_timer()

#Fit the training data set to the decision tree model
india_decision_tree.fit(x_train_simple, y_train.values.ravel()).predict(x_test_simple)

#Predict the presence of heart disese by inputting the test data into the india_decision_tre
target_pred_decision_tree = india_decision_tree.predict(x_test_simple)

#Stop timing of fitting and prediction process
end_time = timeit.default_timer()

#Calculate total time
computational_time = end_time - start_time
#Calculate memory usage in megabytes
memory_usage = round(psutil.Process().memory_info().rss/ (1024 * 1024),2)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score, matthew

accuracy_decision_tree =  round(accuracy_score(y_test, target_pred_decision_tree),4)*100
precision_decision_tree = round(precision_score(y_test, target_pred_decision_tree, pos_label
recall_decision_tree = round(recall_score(y_test, target_pred_decision_tree, pos_label=1),3)
f1_score_decision_tree = round(f1_score(y_test, target_pred_decision_tree, pos_label=1),3)
mcc_decision_tree = round(matthews_corrcoef(y_test, target_pred_decision_tree),3)
specificity_decision_tree = round(recall_score(y_test, target_pred_decision_tree, pos_label=

#Organize performance metrics into a list
performance_decision_tree = [["Decision Tree", accuracy_decision_tree, specificity_decision_

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_decision_tree, columns=['Model', 'Accuracy', '
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_decision_tree = performance_metrics

performance_metrics
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC	Computational Speed	Memory Usage

```
#Import GridSearchCV class from sklearn library for hyperparameter tuning
from sklearn.model_selection import GridSearchCV

#Initialize the decision tree classifier
india_decision_tree = DecisionTreeClassifier(random_state=42)

#A parameter grid was created using the defaults and selected integers
param_grid = {'criterion': ['gini', 'entropy'],
              'max_depth': [None, 1,2,10, 20, 30],
              'min_samples_split': [2, 5, 10,15,18],
              'min_samples_leaf': [1, 2, 4]}

#Initialize the GridSearchCV class using the decision model, the parameter grid and a 10-fol
grid_india_dt = GridSearchCV(india_decision_tree , param_grid, cv=10)
grid_india_dt.fit(x_train_simple, y_train)

#Output the best parameters, the model is optimized based on accuracy score
best_params_dt = grid_india_dt.best_params_
print(best_params_dt)

#Fit the model using athe best parameters
india_decision_tree = DecisionTreeClassifier(**best_params_dt, random_state=42)
india_decision_tree.fit(x_train_simple, y_train)

# Use the best model for predictions and recalculate metrics
target_pred_decision_tree = india_decision_tree.predict(x_test_simple)

#Calculate Performance Metrics
accuracy_decision_tree =  round(accuracy_score(y_test, target_pred_decision_tree),4)*100
precision_decision_tree = round(precision_score(y_test, target_pred_decision_tree, pos_label
recall_decision_tree = round(recall_score(y_test, target_pred_decision_tree, pos_label=1), 3
f1_score_decision_tree = round(f1_score(y_test, target_pred_decision_tree, pos_label=1), 3)
mcc_decision_tree = round(matthews_corrcoef(y_test, target_pred_decision_tree), 3)
specificity_decision_tree = round(recall_score(y_test, target_pred_decision_tree, pos_label=

# Organize performance metrics into a list
performance_decision_tree = [["Decision Tree", accuracy_decision_tree, specificity_decision_

# Create a DataFrame of performance metrics
grid_dt_pm = pd.DataFrame(performance_decision_tree, columns=['Model', 'Accuracy', 'Specific
grid_dt_pm.index = [""]

grid_dt_pm

#There are improvements to the metrics with the exception of specificity
```

```
{'criterion': 'entropy', 'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split':
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
from sklearn.tree import DecisionTreeClassifier
import numpy as np

# Initialize the classifier and assign it to the variable. Assign random_state 42 to ensure
india_decision_tree = DecisionTreeClassifier(random_state=42)

# Initialize RepeatedStratifiedKFold (will complete 30 rounds in total)
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_decision_tree.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_decision_tree = india_decision_tree.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_decision_tree)*100,2)
    precision_list.append(round(precision_score(y_test_fold, target_pred_decision_tree, pos_
    recall_list.append(round(recall_score(y_test_fold, target_pred_decision_tree, pos_label=
    f1_list.append(round(f1_score(y_test_fold, target_pred_decision_tree, pos_label=1)*100,2
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_decision_tree)*100,2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_decision_tree, pos_l

#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
mean_metrics = round(performance_metrics_fold.mean(),2)
```

```
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
Mean Metrics:
Accuracy       95.50
Precision      95.89
Recall         96.44
F1 Score       96.13
MCC            90.84
Specificity    94.21
dtype: float64

Standard Deviation Metrics:
Accuracy       2.05
Precision      2.41
Recall         2.56
F1 Score       1.76
MCC            4.18
Specificity    3.52
dtype: float64
```

```
#Repeat classifier and calculate performance metrics using only selected features

#Random Forest

from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier

#Import classes to calculate memory consumption and runtime
import timeit
import psutil

#Initialize the classifier and assign to variable. Assign random_state 0 to reproduce result
india_random_forest = RandomForestClassifier(random_state=42)

#Begin timing of fitting and prediction process
start_time = timeit.default_timer()

#Fit the training data set to the decision tree model
india_random_forest.fit(x_train_simple, y_train.values.ravel()).predict(x_test_simple)

#Predict the presence of heart disese by inputting the test data into the india_random_fores
target_pred_random_forest = india_random_forest.predict(x_test_simple)

#Stop timing of fitting and prediction process
end_time = timeit.default_timer()

#Calculate total time
computational_time = end_time - start_time
#Calculate memory usage in megabytes
memory_usage = round(psutil.Process().memory_info().rss/ (1024 * 1024),2)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score, matthew

accuracy_random_forest =  round(accuracy_score(y_test, target_pred_random_forest),4)*100
precision_random_forest = round(precision_score(y_test, target_pred_random_forest, pos_label
recall_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=1),3)
f1_score_random_forest = round(f1_score(y_test, target_pred_random_forest, pos_label=1),3)
mcc_random_forest = round(matthews_corrcoef(y_test, target_pred_random_forest),3)
specificity_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=

#Organize performance metrics into a list
performance_random_forest = [["Random Forest", accuracy_random_forest, specificity_random_fo

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_random_forest, columns=['Model', 'Accuracy', '
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_random_forest = performance_metrics

performance_metrics
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC	Computational Speed	Memory Usage

```
#Import GridSearchCV class from sklearn library for hyperparameter tuning
from sklearn.model_selection import GridSearchCV

#Initialize the random forest classifier and assign to variable india_random_forest. Assign
india_random_forest = RandomForestClassifier(random_state=42)

#A parameter grid was created using the defaults and selected integers to cycle through in c
#These features were selected based on the values available in the sklearn documentation
param_grid = {'n_estimators': [25, 50, 100, 150],
              'max_features': ['sqrt', 'log2', None],
              'max_depth': [3, 6, 9],
              'max_leaf_nodes': [3, 6, 9]}

#Initialize the GridSearchCV class using the random forest, the parameter grid and a 10-folc
grid_india_rf = GridSearchCV(india_random_forest , param_grid, cv=10)
grid_india_rf.fit(x_train_simple, y_train.values.ravel())

#Output the best parameters, the model is optimized based on accuracy score
best_params_rf = grid_india_rf.best_params_
print(best_params_rf)

#Fit the model using athe best parameters
india_random_forest = RandomForestClassifier(**best_params_dt, random_state=42)
india_random_forest.fit(x_train_simple, y_train.values.ravel())

# Use the best model for predictions and recalculate metrics
target_pred_random_forest = india_random_forest.predict(x_test_simple)

#Calculate Performance Metrics
accuracy_random_forest =  round(accuracy_score(y_test, target_pred_random_forest),4)*100
precision_random_forest = round(precision_score(y_test, target_pred_random_forest, pos_label
recall_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=1),3)
f1_score_random_forest = round(f1_score(y_test, target_pred_random_forest, pos_label=1),3)
mcc_random_forest = round(matthews_corrcoef(y_test, target_pred_random_forest),3)
specificity_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=

# Organize performance metrics into a list
performance_random_forest = [["Random Forest", accuracy_random_forest, specificity_random_fo

# Create a DataFrame of performance metrics
grid_rf_pm = pd.DataFrame(performance_random_forest, columns=['Model', 'Accuracy', 'Specific
grid_rf_pm.index = [""]

grid_rf_pm
```

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
import numpy as np

# Initialize the classifier and assign it to the variable. Assign random_state 42 to ensure
india_random_forest = RandomForestClassifier(random_state=42)

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_random_forest.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_random_forest= india_random_forest.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_random_forest)*100,2)
    precision_list.append(round(precision_score(y_test_fold, target_pred_random_forest, pos_
    recall_list.append(round(recall_score(y_test_fold, target_pred_random_forest, pos_label=
    f1_list.append(round(f1_score(y_test_fold, target_pred_random_forest, pos_label=1)*100,2
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_random_forest)*100,2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_random_forest, pos_l


#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
mean_metrics = round(performance_metrics_fold.mean(),2)
```

```
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
Mean Metrics:
Accuracy       97.30
Precision      97.46
Recall         97.93
F1 Score       97.68
MCC            94.49
Specificity    96.43
dtype: float64

Standard Deviation Metrics:
Accuracy       1.78
Precision      1.95
Recall         1.83
F1 Score       1.53
MCC            3.66
Specificity    2.78
dtype: float64
```

```
#Repeat classifier and calculate performance metrics using only selected features

#Naive Bayes

#The application of Naive Bayes in the paper is unclear. The dataset contains both categoric
#Here we will applying different Naive Bayes classifiers to the categorical and numerical fe
from sklearn.naive_bayes import  CategoricalNB, GaussianNB

#Import classes to calculate memory consumption and runtime
import timeit
import psutil

#Initialize the naive bayes models and assign to variable
india_naive_numerical = GaussianNB()
india_naive_categorical = CategoricalNB()

#List categorical and numerical feature names
india_categorical_nb = ['fastingbloodsugar','chestpain_1', 'chestpain_2', 'chestpain_3', 're
india_numerical_nb = ['restingBP', 'serumcholestrol', 'maxheartrate', 'oldpeak']

#Begin timing of fitting and prediction process
start_time = timeit.default_timer()

# Fit the categorical features in the training data set to the categorical naive bayes model
india_naive_categorical.fit(x_train_simple[india_categorical_nb], y_train.values.ravel())

#Fit the numerical features in the training data set to the gaussian naive bayes model
india_naive_numerical.fit(x_train_simple[india_numerical_nb], y_train.values.ravel())

# Predict probabilities for using categorical and numerical features
probability_categorical = india_naive_categorical.predict_proba(x_test_simple[india_categori
probability_numerical= india_naive_numerical.predict_proba(x_test_simple[india_numerical_nb]

#Combine the probabilities using the product rule
total_probability = probability_categorical * probability_numerical

#We can use this code to select the class that has the greatest probability for a given row
import numpy as np
target_pred_naive = np.argmax(total_probability, axis=1)

#Stop timing of fitting and prediction process
end_time = timeit.default_timer()

#Calculate total time
computational_time = end_time - start_time
#Calculate memory usage in megabytes
memory_usage = round(psutil.Process().memory_info().rss/ (1024 * 1024),2)

#Calculate performance metrics
accuracy_naive =  round(accuracy_score(y_test, target_pred_naive),4)*100
precision_naive = round(precision_score(y_test, target_pred_naive, pos_label=1),3)
```

```
recall_naive = round(recall_score(y_test, target_pred_naive, pos_label=1),3)
f1_score_naive = round(f1_score(y_test, target_pred_naive, pos_label=1),3)
mcc_naive = round(matthews_corrcoef(y_test, target_pred_naive),3)
specificity_naive = round(recall_score(y_test, target_pred_naive, pos_label=0),3)

#Organize performance metrics into a list
performance_naive = [["Naive Bayes", accuracy_naive,specificity_naive,precision_naive,recall

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_naive, columns=['Model', 'Accuracy', 'Specific
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_naive_bayes = performance_metrics

performance_metrics
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC	Computational Speed	Memory Usage
Naive	94.0	0.911	0.93	0.964	0.947	0.879	0.024183	203.19

```
from sklearn.model_selection import StratifiedKFold
from sklearn.naive_bayes import CategoricalNB, GaussianNB

#List categorical and numerical feature names
india_categorical_nb = ['fastingbloodsugar','chestpain_1', 'chestpain_2', 'chestpain_3', 're
india_numerical_nb = ['restingBP', 'serumcholestrol', 'maxheartrate', 'oldpeak']

# Initialize Naive Bayes models and assign to variables
india_naive_categorical = CategoricalNB()
india_naive_numerical = GaussianNB()

# Combine categorical and numerical features
x_naive = x_simple[india_categorical_nb + india_numerical_nb]

# Initialize StratifiedKFold
cv = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)

# Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

# Iterate through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_naive, y_simple):
    # Start by grouping training and testing features based on training and testing row indi
    x_train_fold, x_test_fold = x_naive.iloc[train_index], x_naive.iloc[test_index]
    # Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    # Fit the training data set to the categorical and numerical Naive Bayes models
    india_naive_categorical.fit(x_train_fold[india_categorical_nb], y_train_fold.values.rave
    india_naive_numerical.fit(x_train_fold[india_numerical_nb], y_train_fold.values.ravel())

    # Predict probabilities for using categorical and numerical features
    probability_categorical = india_naive_categorical.predict_proba(x_test_fold[india_catego
    probability_numerical = india_naive_numerical.predict_proba(x_test_fold[india_numerical_

    # Combine the probabilities using the product rule
    total_probability = probability_categorical * probability_numerical

    # Use this code to select the class that has the greatest probability for a given row
    target_pred_naive = np.argmax(total_probability, axis=1)

    # Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_naive) * 100, 2))
    precision_list.append(round(precision_score(y_test_fold, target_pred_naive, pos_label=1)
    recall_list.append(round(recall_score(y_test_fold, target_pred_naive, pos_label=1) * 10
    f1_list.append(round(f1_score(y_test_fold, target_pred_naive, pos_label=1) * 100, 2))
```

```
        mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_naive) * 100, 2))
        specificity_list.append(round(recall_score(y_test_fold, target_pred_naive, pos_label=0)

    # Create a DataFrame to store metrics for each fold
    performance_metrics_naive = pd.DataFrame({
        'Accuracy': accuracy_list,
        'Precision': precision_list,
        'Recall': recall_list,
        'F1 Score': f1_list,
        'MCC': mcc_list,
        'Specificity': specificity_list
    })

    # Calculate mean and standard deviation across folds
    mean_metrics_naive = round(performance_metrics_naive.mean(), 2)
    std_metrics_naive = round(performance_metrics_naive.std(), 2)

    # Display mean and standard deviation
    print('Mean Metrics:')
    print(mean_metrics_naive)
    print('\nStandard Deviation Metrics:')
    print(std_metrics_naive)

    # performance_metrics_naive
```

```
#Repeat classifier and calculate performance metrics using only selected features

#Logistic Regression

from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression

#Import classes to calculate memory consumption and runtime
import timeit
import psutil

#Initialize the classifier and assign to variable. Assign random_state 0 to reproduce result
india_logistic_reg = LogisticRegression(random_state=42)

#Begin timing of fitting and prediction process
start_time = timeit.default_timer()

#Fit the training data set to the decision tree model
india_logistic_reg.fit(x_train_simple, y_train.values.ravel()).predict(x_test_simple)

#Predict the presence of heart disese by inputting the test data into the india_logistic_reg
target_pred_logistic_reg = india_logistic_reg.predict(x_test_simple)

#Stop timing of fitting and prediction process
end_time = timeit.default_timer()

#Calculate total time
computational_time = end_time - start_time
#Calculate memory usage in megabytes
memory_usage = round(psutil.Process().memory_info().rss/ (1024 * 1024),2)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score, matthew

accuracy_logistic_reg =  round(accuracy_score(y_test, target_pred_logistic_reg),4)*100
precision_logistic_reg = round(precision_score(y_test, target_pred_logistic_reg, pos_label=1
recall_logistic_reg = round(recall_score(y_test, target_pred_logistic_reg, pos_label=1),3)
f1_score_logistic_reg = round(f1_score(y_test, target_pred_logistic_reg, pos_label=1),3)
mcc_logistic_reg = round(matthews_corrcoef(y_test, target_pred_logistic_reg),3)
specificity_logistic_reg = round(recall_score(y_test, target_pred_logistic_reg, pos_label=0)

#Organize performance metrics into a list
performance_logistic_reg = [["Logistic Regression", accuracy_logistic_reg, specificity_logis

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_logistic_reg, columns=['Model', 'Accuracy', 'S
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_logistic_reg = performance_metrics

performance_metrics
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC	Computational Speed	Memor Usag

```
# Import GridSearchCV class from sklearn library for hyperparameter tuning
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

# Initialize the logistic regression classifier and assign it to the variable india_logistic
india_logistic_reg = LogisticRegression(random_state=42)

# A parameter grid for logistic regression
param_grid = {'max_iter':[100,110,120,130,140],
              'C' : [1.0,1.5,2.0,2.5]}

# Initialize the GridSearchCV class using the logistic regression model, the parameter grid,
grid_india_lr = GridSearchCV(india_logistic_reg, param_grid, cv=10)
grid_india_lr.fit(x_train_simple, y_train.values.ravel())

# Output the best parameters based on accuracy score
best_params_lr = grid_india_lr.best_params_
print(best_params_lr)

#Fit the model using the best parameters
india_logistic_reg = LogisticRegression(**best_params_lr, random_state=42)
india_logistic_reg.fit(x_train_simple, y_train.values.ravel())

#Use the best model to calculate predictions
target_pred_logistic_reg = india_logistic_reg.predict(x_test_simple)

# Calculate Performance Metrics
accuracy_logistic_reg = round(accuracy_score(y_test, target_pred_logistic_reg), 4) * 100
precision_logistic_reg = round(precision_score(y_test, target_pred_logistic_reg, pos_label=1
recall_logistic_reg = round(recall_score(y_test, target_pred_logistic_reg, pos_label=1), 3)
f1_score_logistic_reg = round(f1_score(y_test, target_pred_logistic_reg, pos_label=1), 3)
mcc_logistic_reg = round(matthews_corrcoef(y_test, target_pred_logistic_reg), 3)
specificity_logistic_reg = round(recall_score(y_test, target_pred_logistic_reg, pos_label=0)

# Organize performance metrics into a list
performance_logistic_reg = [["Logistic Regression", accuracy_logistic_reg, specificity_logis

# Create a DataFrame of performance metrics
grid_lr_pm = pd.DataFrame(performance_logistic_reg, columns=['Model', 'Accuracy', 'Specifici
grid_lr_pm.index = [""]

grid_lr_pm
```

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
from sklearn.linear_model import LogisticRegression
import numpy as np

#Initialize the classifier and assign to variable. Assign random_state 0 to reproduce result
india_logistic_reg = LogisticRegression(C= 1.0, max_iter= 100, random_state=42)

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_logistic_reg.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_logistic_reg= india_logistic_reg.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_logistic_reg)*100,2))
    precision_list.append(round(precision_score(y_test_fold, target_pred_logistic_reg, pos_l
    recall_list.append(round(recall_score(y_test_fold, target_pred_logistic_reg, pos_label=1
    f1_list.append(round(f1_score(y_test_fold, target_pred_logistic_reg, pos_label=1)*100,2)
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_logistic_reg)*100,2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_logistic_reg, pos_la


#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
```

```
mean_metrics = round(performance_metrics_fold.mean(),2)
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
#Repeat classifier and calculate performance metrics using only selected features

#Support Vector Machine

from sklearn.model_selection import cross_val_score
from sklearn import svm

#Import classes to calculate memory consumption and runtime
import timeit
import psutil

#Initialize the support vector machine classifier and assign to variable india_decision_tree
india_support_vector = svm.SVC(kernel='linear', random_state=42)

#Begin timing of fitting and prediction process
start_time = timeit.default_timer()

#Fit the training data set to the decision tree model
india_support_vector.fit(x_train_simple, y_train.values.ravel()).predict(x_test_simple)

#Predict the presence of heart disese by inputting the test data into the model
target_pred_support_vector = india_support_vector.predict(x_test_simple)

#Stop timing of fitting and prediction process
end_time = timeit.default_timer()

#Calculate total time
computational_time = end_time - start_time
#Calculate memory usage in megabytes
memory_usage = round(psutil.Process().memory_info().rss/ (1024 * 1024),2)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score, matthew

accuracy_support_vector =  round(accuracy_score(y_test, target_pred_support_vector),4)*100
precision_support_vector = round(precision_score(y_test, target_pred_support_vector, pos_lab
recall_support_vector = round(recall_score(y_test, target_pred_support_vector, pos_label=1),
f1_score_support_vector = round(f1_score(y_test, target_pred_support_vector, pos_label=1),3)
mcc_support_vector = round(matthews_corrcoef(y_test, target_pred_support_vector),3)
specificity_support_vector = round(recall_score(y_test, target_pred_support_vector, pos_labe

#Organize performance metrics into a list
performance_support_vector = [["Support Vector", accuracy_support_vector, specificity_suppor

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_support_vector, columns=['Model', 'Accuracy',
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_support_vector = performance_metrics

performance_metrics
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC	Computational Speed	Memory Usage
Support	95.25	0.939	0.951	0.964	0.957	0.904	0.021854	204.37

```
# Import GridSearchCV class from sklearn library for hyperparameter tuning
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

# Initialize the SVM classifier and assign it to the variable india_svm. Assign random_state
india_svm = SVC(random_state=42)

# A parameter grid for SVM
param_grid = {
    'C': [0.1, 1, 10, 100],
    'kernel': ['linear', 'rbf', 'poly', 'sigmoid'],
    'degree': [2, 3, 4],
    'gamma': ['scale', 'auto']
}

# Initialize the GridSearchCV class using the SVM model, the parameter grid, and a 10-fold c
grid_india_svm = GridSearchCV(india_svm, param_grid, cv=10)
grid_india_svm.fit(x_train_simple, y_train.values.ravel())

# Output the best parameters based on accuracy score
best_params_svm = grid_india_svm.best_params_
print(best_params_svm)

# Fit the model using the best parameters
india_svm = SVC(**best_params_svm, random_state=42)
india_svm.fit(x_train_simple, y_train.values.ravel())

# Use the best model to calculate predictions
target_pred_svm = india_svm.predict(x_test_simple)

# Calculate Performance Metrics
accuracy_svm = round(accuracy_score(y_test, target_pred_svm), 4) * 100
precision_svm = round(precision_score(y_test, target_pred_svm, pos_label=1), 3)
recall_svm = round(recall_score(y_test, target_pred_svm, pos_label=1), 3)
f1_score_svm = round(f1_score(y_test, target_pred_svm, pos_label=1), 3)
mcc_svm = round(matthews_corrcoef(y_test, target_pred_svm), 3)
specificity_svm = round(recall_score(y_test, target_pred_svm, pos_label=0), 3)

# Organize performance metrics into a list
performance_svm = [["Support Vector Machine", accuracy_svm, specificity_svm, precision_svm,

# Create a DataFrame of performance metrics
grid_svm_pm = pd.DataFrame(performance_svm, columns=['Model', 'Accuracy', 'Specificity', 'Pr
grid_svm_pm.index = [""]

grid_svm_pm
```

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
from sklearn import svm
import numpy as np

#Initialize the classifier and assign to variable. Assign random_state 0 to reproduce result
india_support_vector = svm.SVC(kernel='linear', random_state=42)

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_support_vector.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_support_vector= india_support_vector.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_support_vector)*100,2
    precision_list.append(round(precision_score(y_test_fold, target_pred_support_vector, pos
    recall_list.append(round(recall_score(y_test_fold, target_pred_support_vector, pos_label
    f1_list.append(round(f1_score(y_test_fold, target_pred_support_vector, pos_label=1)*100,
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_support_vector)*100,2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_support_vector, pos_

#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
mean_metrics = round(performance_metrics_fold.mean(),2)
```

```
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
#Repeat classifier and calculate performance metrics using only selected features

#Gradient Boosting

#Import gradient boosting classifier from scikit-learn libraries
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import cross_val_score

#Import classes to calculate memory consumption and runtime
import timeit
import psutil

#Initialize the support vector machine classifier and assign to variable. Assign random_stat
india_gradient = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0, max_depth=1

#Begin timing of fitting and prediction process
start_time = timeit.default_timer()

#Fit the training data set to the decision tree model
india_gradient.fit(x_train_simple, y_train.values.ravel()).predict(x_test_simple)

#Predict the presence of heart disese by inputting the test data into the model
target_pred_gradient = india_gradient.predict(x_test_simple)

#Stop timing of fitting and prediction process
end_time = timeit.default_timer()

#Calculate total time
computational_time = end_time - start_time
#Calculate memory usage in megabytes
memory_usage = round(psutil.Process().memory_info().rss/ (1024 * 1024),2)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score, matthew

accuracy_gradient =  round(accuracy_score(y_test, target_pred_gradient),4)*100
precision_gradient = round(precision_score(y_test, target_pred_gradient, pos_label=1),3)
recall_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=1),3)
f1_score_gradient = round(f1_score(y_test, target_pred_gradient, pos_label=1),3)
mcc_gradient = round(matthews_corrcoef(y_test, target_pred_gradient),3)
specificity_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=0),3)

#Organize performance metrics into a list
performance_gradient = [["Gradient", accuracy_gradient, specificity_gradient,precision_gradi

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_gradient, columns=['Model', 'Accuracy', 'Speci
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_gradient = performance_metrics
```

```
performance_metrics
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC	Computational Speed	Memory Usage
Gradient	97.0	0.944	0.956	0.991	0.973	0.94	0.101133	204.37

```
#Gradient Boosting

#Initialize the gradient boosting classifier and assign to variable india_gradient. Assign r
india_gradient = GradientBoostingClassifier(random_state=42)

#A parameter grid was created using selected integers to cycle through in order to optimize
#These features were selected based on the values available in the sklearn documentation
param_dist = {'n_estimators': [50, 100, 200],
              'learning_rate': [0.01, 0.1, 0.2],
              'max_depth': [3, 4, 5],
              'min_samples_split': [2, 5, 10],
              'min_samples_leaf': [1, 2, 4]}

#Fit the training data set to the support vector machine classifier
india_gradient.fit(x_train, y_train.values.ravel()).predict(x_test)

#Initialize the GridSearchCV class using the gradient boosting, the parameter grid and a 10-
grid_india_gb = GridSearchCV(india_gradient, param_dist, cv=10)
grid_india_gb.fit(x_train_simple, y_train.values.ravel())

#Output the best parameters, the model is optimized based on accuracy score
best_params_gb = grid_india_gb.best_params_
print(best_params_gb)

#Fit the model using athe best parameters
india_gradient= GradientBoostingClassifier(**best_params_gb, random_state=42)
india_gradient.fit(x_train_simple, y_train.values.ravel())

#Predict the presence of heart disese by inputting the test data into the india_gradient
target_pred_gradient = india_gradient.predict(x_test_simple)

accuracy_gradient =  round(accuracy_score(y_test, target_pred_gradient),4)*100
precision_gradient = round(precision_score(y_test, target_pred_gradient, pos_label=1),3)
recall_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=1),3)
f1_score_gradient = round(f1_score(y_test, target_pred_gradient, pos_label=1),3)
mcc_gradient = round(matthews_corrcoef(y_test, target_pred_gradient),3)
specificity_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=0),3)

#Organize performance metrics into a list
performance_gradient = [["Gradient Boosting", accuracy_gradient,specificity_gradient,precisi

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_gradient, columns=['Model', 'Accuracy','Specif
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_gradient = performance_metrics

performance_metrics
```

```
{'learning_rate': 0.1, 'max_depth': 3, 'min_samples_leaf': 1, 'min_samples_split': 10, '
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
Gradient Boosting	97.25	0.966	0.972	0.977	0.975	0.944

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
from sklearn.ensemble import GradientBoostingClassifier
import numpy as np

#Initialize the classifier and assign to variable. Assign random_state 0 to reproduce result
india_gradient = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0, max_depth=1

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_gradient.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_gradient= india_gradient.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_gradient)*100,2))
    precision_list.append(round(precision_score(y_test_fold, target_pred_gradient, pos_label
    recall_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=1)*10
    f1_list.append(round(f1_score(y_test_fold, target_pred_gradient, pos_label=1)*100,2))
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_gradient)*100,2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=

#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
mean_metrics = round(performance_metrics_fold.mean(),2)
```

```
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
Mean Metrics:
Accuracy       97.17
Precision      97.95
Recall         97.18
F1 Score       97.55
MCC            94.23
Specificity    97.14
dtype: float64

Standard Deviation Metrics:
Accuracy       1.58
Precision      1.78
Recall         1.89
F1 Score       1.36
MCC            3.22
Specificity    2.53
dtype: float64
```

```
#Repeat classifier and calculate performance metrics using only selected features

#XGBoost

#Import xgb boosting classifier from scikit-learn libraries
import xgboost as xgb
from sklearn.model_selection import cross_val_score

#Import classes to calculate memory consumption and runtime
import timeit
import psutil

#Initialize the classifier and assign to variable. Assign random_state 0 to reproduce result
india_xgb = xgb.XGBClassifier(n_estimators=100, objective='binary:logistic', tree_method='hi

#Begin timing of fitting and prediction process
start_time = timeit.default_timer()

#Fit the training data set to the decision tree model
india_xgb.fit(x_train_simple, y_train.values.ravel()).predict(x_test_simple)

#Predict the presence of heart disese by inputting the test data into the model
target_pred_xgb = india_xgb.predict(x_test_simple)

#Stop timing of fitting and prediction process
end_time = timeit.default_timer()

#Calculate total time
computational_time = end_time - start_time
#Calculate memory usage in megabytes
memory_usage = round(psutil.Process().memory_info().rss/ (1024 * 1024),2)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score, matthew

accuracy_xgb =  round(accuracy_score(y_test, target_pred_xgb),4)*100
precision_xgb = round(precision_score(y_test, target_pred_xgb, pos_label=1),3)
recall_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=1),3)
f1_score_xgb = round(f1_score(y_test, target_pred_xgb, pos_label=1),3)
mcc_xgb = round(matthews_corrcoef(y_test, target_pred_xgb),3)
specificity_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=0),3)

#Organize performance metrics into a list
performance_xgb = [["XGBoost", accuracy_xgb, specificity_xgb,precision_xgb,recall_xgb,f1_scc

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_xgb, columns=['Model', 'Accuracy', 'Specificit
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_xgb = performance_metrics
```

```
performance_metrics
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC	Computational Speed	Memory Usage

```
#XGBoost

#Initialize the support vector machine classifier and assign to variable india_decision_tree
india_xgb = xgb.XGBClassifier(enable_categorical=True, seed= 42)

#A parameter grid was created using the defaults and selected integers to cycle through in c
#These features were selected based on the values available in the sklearn documentation
param_grid = {
    'n_estimators': [50, 100, 200],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 4, 5],
    'subsample': [0.8, 0.9, 1.0],
    'colsample_bytree': [0.8, 0.9, 1.0]
}

#Initialize the RandomizedSearchCV class using the decision model, the parameter grid and a
grid_india_xgb = GridSearchCV(india_xgb , param_grid, cv=10)
grid_india_xgb.fit(x_train_simple, y_train.values.ravel())

#Output the best parameters, the model is optimized based on accuracy score
best_params_xgb = grid_india_xgb.best_params_
print(best_params_xgb)

#Fit the model using athe best parameters
india_xgb = xgb.XGBClassifier(**best_params_xgb, seed=42)
india_xgb.fit(x_train_simple, y_train.values.ravel())

# Use the best model for predictions and recalculate metrics
target_pred_random_forest = india_xgb.predict(x_test_simple)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score

accuracy_xgb =  round(accuracy_score(y_test, target_pred_xgb),4)*100
precision_xgb = round(precision_score(y_test, target_pred_xgb, pos_label=1),3)
recall_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=1),3)
f1_score_xgb = round(f1_score(y_test, target_pred_xgb, pos_label=1),3)
mcc_xgb = round(matthews_corrcoef(y_test, target_pred_xgb),3)
specificity_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=0),3)

#Organize performance metrics into a list
performance_xgb = [["XGBoost", accuracy_xgb,specificity_xgb,precision_xgb,recall_xgb,f1_scor

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_xgb, columns=['Model', 'Accuracy','Specificity
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_xgb= performance_metrics

performance_metrics
```

```
{'colsample_bytree': 1.0, 'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 50, 'sub
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
XGBoost	96.75	0.95	0.96	0.982	0.971	0.934

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
import xgboost as xgb
import numpy as np

#Initialize the classifier and assign to variable india_decision_tree. Assign random_state 0
india_xgb = xgb.XGBClassifier(n_estimators=100, objective='binary:logistic', tree_method='hi

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_gradient.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_gradient= india_gradient.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_gradient)*100,2))
    precision_list.append(round(precision_score(y_test_fold, target_pred_gradient, pos_label
    recall_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=1),2)
    f1_list.append(round(f1_score(y_test_fold, target_pred_gradient, pos_label=1),2))
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_gradient),2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=

#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
mean_metrics = round(performance_metrics_fold.mean(),2)
```

```
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
Mean Metrics:
Accuracy       97.17
Precision       0.98
Recall          0.97
F1 Score        0.97
MCC             0.94
Specificity     0.97
dtype: float64

Standard Deviation Metrics:
Accuracy       1.58
Precision      0.02
Recall         0.02
F1 Score       0.01
MCC            0.03
Specificity    0.03
dtype: float64
```

```
#Ensemble Model

#Import VotingClassifier to combine model predictions
from sklearn.ensemble import VotingClassifier


# Initialize remaining classifier types and fit the entire training setata
ensemble_random_forest = RandomForestClassifier(random_state = 42)
ensemble_random_forest.fit(x_train_simple, y_train.values.ravel())


ensemble_gradient = GradientBoostingClassifier(random_state = 42)
ensemble_gradient.fit(x_train_simple, y_train.values.ravel())

#Specify Algorithms and initialize ensemble model using a soft voting classifier
algorithms = [('ensemble_random_forest',ensemble_random_forest),('ensemble_gradient',ensembl
ensemble = VotingClassifier(estimators=algorithms, voting='soft')

#Begin timing of fitting and prediction process
start_time = timeit.default_timer()

#Now we can fit each model to voting classifier instance, selecting the categorical variable
ensemble.fit(
    np.column_stack([ensemble_gradient.predict_proba(x_train_simple),
                     ensemble_random_forest.predict_proba(x_train_simple)]),
    y_train.values.ravel()
)

#With the ensemble model, we can make predictions on the target values
target_pred_ensemble = ensemble.predict(
    np.column_stack([ensemble_gradient.predict_proba(x_test_simple),
                     ensemble_random_forest.predict_proba(x_test_simple)])
)

#Stop timing of fitting and prediction process
end_time = timeit.default_timer()

#Calculate total time
computational_time = end_time - start_time
#Calculate memory usage in megabytes
memory_usage = round(psutil.Process().memory_info().rss/ (1024 * 1024),2)

accuracy_ensemble =  round(accuracy_score(y_test, target_pred_ensemble),4)*100
precision_ensemble = round(precision_score(y_test, target_pred_ensemble, pos_label=1),3)
recall_ensemble = round(recall_score(y_test, target_pred_ensemble, pos_label=1),3)
f1_score_ensemble = round(f1_score(y_test, target_pred_ensemble, pos_label=1),3)
mcc_ensemble = round(matthews_corrcoef(y_test, target_pred_ensemble),3)
specificity_ensemble = round(recall_score(y_test, target_pred_ensemble, pos_label=0),3)

#Organize performance metrics into a list
performance_ensemble = [["Ensemble", accuracy_ensemble,specificity_ensemble,precision_ensemb
```

```
#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_ensemble, columns=['Model', 'Accuracy','Specif
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_ensemble = performance_metrics

performance_metrics
```

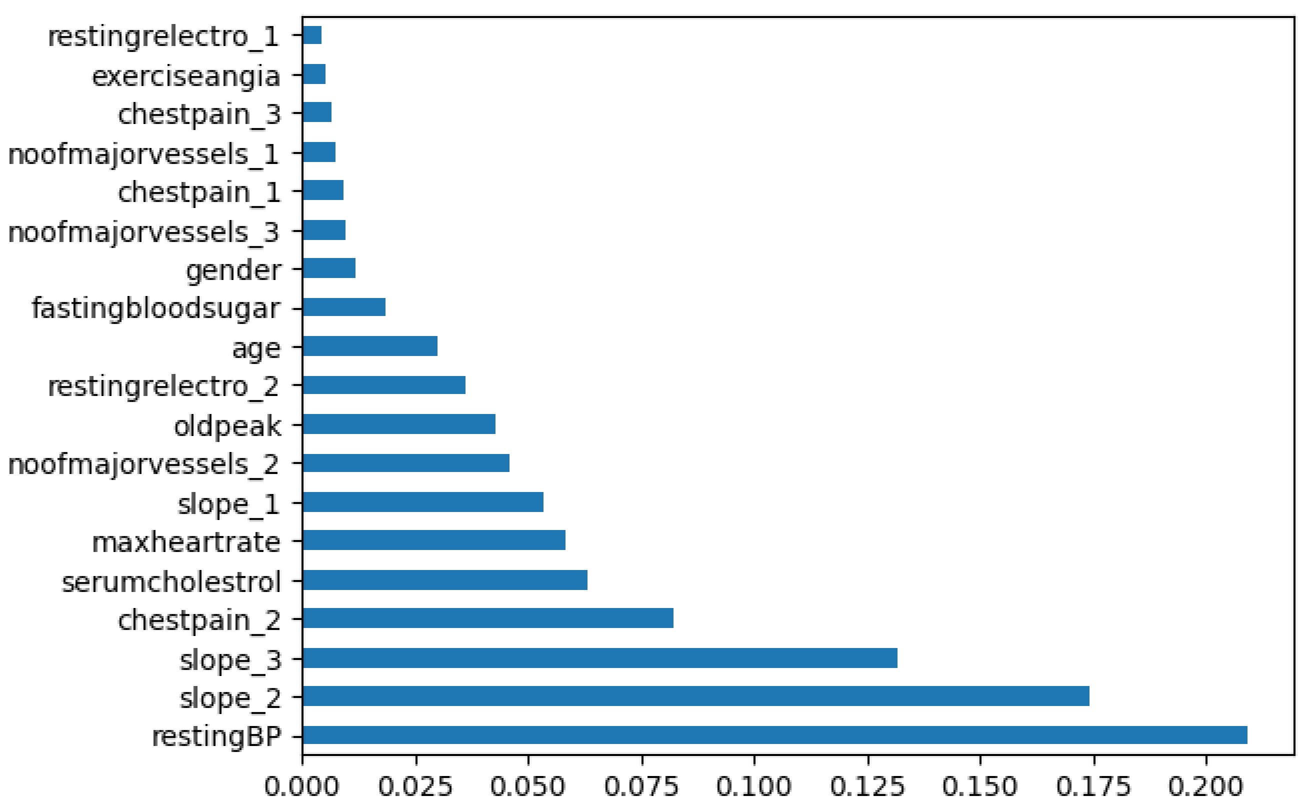
Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC	Computational Speed	Memory Usage

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
from sklearn.ensemble import VotingClassifier
from sklearn.naive_bayes import CategoricalNB, GaussianNB
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, matthew

# Initialize classifiers

ensemble_random_forest = RandomForestClassifier(random_state=42)
ensemble_gradient = GradientBoostingClassifier(random_state=42)

# Specify Algorithms and initialize ensemble model using a soft voting classifier
algorithms = [('ensemble_random_forest', ensemble_random_forest),('ensemble_gradient', ensem

ensemble = VotingClassifier(estimators=algorithms, voting='soft')

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

# Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

# We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    # Start by grouping training and testing features based on training and testing row indi
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    # Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]



    # Fit the entire training set
    ensemble_random_forest.fit(x_train_fold, y_train_fold.values.ravel())
    ensemble_gradient.fit(x_train_fold, y_train_fold.values.ravel())

    #Specify Algorithms and initialize ensemble model using a soft voting classifier
    algorithms = [('ensemble_random_forest',ensemble_random_forest),('ensemble_gradient',ens
    ensemble = VotingClassifier(estimators=algorithms, voting='soft')

    #Now we can fit each model to voting classifier instance, selecting the categorical vari
    ensemble.fit(np.column_stack([ensemble_random_forest.predict_proba(x_train_fold),ensembl

    #With the ensemble model, we can make predictions on the target values
    target_pred_ensemble = ensemble.predict(np.column_stack([ensemble_random_forest.predict_

    #Calculate performance metrics for the current fold
```

```
        accuracy_list.append(accuracy_score(y_test_fold, target_pred_ensemble))
        precision_list.append(precision_score(y_test_fold, target_pred_ensemble, pos_label=1))
        recall_list.append(recall_score(y_test_fold, target_pred_ensemble, pos_label=1))
        f1_list.append(f1_score(y_test_fold, target_pred_ensemble, pos_label=1))
        mcc_list.append(matthews_corrcoef(y_test_fold, target_pred_ensemble))
        specificity_list.append(recall_score(y_test_fold, target_pred_ensemble, pos_label=0))

    #Create a DataFrame to store metrics for each fold and repeat
    performance_metrics_fold = pd.DataFrame({
        'Accuracy': accuracy_list,
        'Precision': precision_list,
        'Recall': recall_list,
        'F1 Score': f1_list,
        'MCC': mcc_list,
        'Specificity': specificity_list
    })

    #Calculate mean and standard deviation across folds and repeats
    mean_metrics = performance_metrics_fold.mean()
    std_metrics = performance_metrics_fold.std()

    #Display mean and standard deviation
    print('Mean Metrics:')
    print(mean_metrics)
    print('\nStandard Deviation Metrics:')
    print(std_metrics)

    #performance_metrics_fold
```

```
Mean Metrics:
Accuracy       0.973000
Precision      0.978336
Recall         0.975287
F1 Score       0.976658
MCC            0.945049
Specificity    0.969841
dtype: float64

Standard Deviation Metrics:
Accuracy       0.016640
Precision      0.017126
Recall         0.020592
F1 Score       0.014410
MCC            0.034002
Specificity    0.024163
dtype: float64
```

```
#Feature Selection using Embedded Methods

#Random Forest Feature Importance Plot
from sklearn.ensemble import RandomForestClassifier

#Initialize the random forest classifier. Assign random_state 42 to reproduce results
random_forest_embedded = RandomForestClassifier(random_state=42)

#Fit the training data set to the random forest classifier
random_forest_embedded.fit(x_train, y_train.values.ravel()).predict(x_test)

#Extract feature importance plot
(pd.Series(random_forest_embedded.feature_importances_, index=x_train.columns)
   .nlargest(20)
   .plot(kind='barh'))

#Based on feature importance plot, all features below slope_1 appear to be most relevant

#Drop least releavnt features from x_train and x_test

#Features to drop based on importance chart
features_remove = ['restingrelectro_1','exerciseangia','chestpain_3','noofmajorvessels_3','g

#Remove selected features from x_train and x_test
x_train_embedded = x_train.drop(columns=features_remove)
x_test_embedded = x_test.drop(columns=features_remove)
```



```
#Remove features from consistent dataset

#Modify consistent dataset for k-fold cross-validation

#Data will be scaled using the robust scaler that is less susceptible to outliers
from sklearn.preprocessing import RobustScaler

#Subset of numerical features
india_numerical =['age', 'restingBP', 'serumcholestrol', 'maxheartrate', 'oldpeak']

#Separate target column
x_simple = data_india_coded.drop(columns=['target'] + features_remove)
y_simple = data_india_coded['target']

#Initialize RobustScaler
scaler = RobustScaler()
#Fit the consistent dataset to the RobustScaler instance.
x_simple[india_numerical] = scaler.fit_transform(x_simple[india_numerical])


#Repeat Random Forest Classifier and Output Statistics
#Initialize the random forest classifier and assign to variable india_random_forest. Assign
india_random_forest = RandomForestClassifier(random_state=42)

#Fit the training data set to the random forest classifier
india_random_forest.fit(x_train_embedded, y_train.values.ravel()).predict(x_test_embedded)

#Predict the presence of heart disese by inputting the test data into the india_random_fores
target_pred_random_forest = india_random_forest.predict(x_test_embedded)

accuracy_random_forest =  round(accuracy_score(y_test, target_pred_random_forest),4)*100
precision_random_forest = round(precision_score(y_test, target_pred_random_forest, pos_label
recall_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=1),3)
f1_score_random_forest = round(f1_score(y_test, target_pred_random_forest, pos_label=1),3)
mcc_random_forest = round(matthews_corrcoef(y_test, target_pred_random_forest),3)
specificity_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=

#Organize performance metrics into a list
performance_random_forest = [["Random Forest", accuracy_random_forest,specificity_random_for

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_random_forest, columns=['Model', 'Accuracy', '
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_random_forest = performance_metrics

performance_metrics
```

Model Accuracy Specificity Precision Recall F1 Score MCC

```
#Import GridSearchCV class from sklearn library for hyperparameter tuning
from sklearn.model_selection import GridSearchCV

#Initialize the random forest classifier and assign to variable india_random_forest. Assign
india_random_forest = RandomForestClassifier(random_state=42)

#A parameter grid was created using the defaults and selected integers to cycle through in c
#These features were selected based on the values available in the sklearn documentation
param_grid = {'n_estimators': [25, 50, 100, 150],
              'max_features': ['sqrt', 'log2', None],
              'max_depth': [3, 6, 9],
              'max_leaf_nodes': [3, 6, 9]}

#Initialize the GridSearchCV class using the random forest, the parameter grid and a 10-folc
grid_india_rf = GridSearchCV(india_random_forest , param_grid, cv=10)
grid_india_rf.fit(x_train_embedded, y_train.values.ravel())

#Output the best parameters, the model is optimized based on accuracy score
best_params_rf = grid_india_rf.best_params_
print(best_params_rf)

#Fit the model using athe best parameters
india_random_forest = RandomForestClassifier(**best_params_dt, random_state=42)
india_random_forest.fit(x_train_embedded, y_train.values.ravel())

# Use the best model for predictions and recalculate metrics
target_pred_random_forest = india_random_forest.predict(x_test_embedded)

#Calculate Performance Metrics
accuracy_random_forest =  round(accuracy_score(y_test, target_pred_random_forest),4)*100
precision_random_forest = round(precision_score(y_test, target_pred_random_forest, pos_label
recall_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=1),3)
f1_score_random_forest = round(f1_score(y_test, target_pred_random_forest, pos_label=1),3)
mcc_random_forest = round(matthews_corrcoef(y_test, target_pred_random_forest),3)
specificity_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=

# Organize performance metrics into a list
performance_random_forest = [["Random Forest", accuracy_random_forest, specificity_random_fc

# Create a DataFrame of performance metrics
grid_rf_pm = pd.DataFrame(performance_random_forest, columns=['Model', 'Accuracy', 'Specific
grid_rf_pm.index = [""]

grid_rf_pm
```

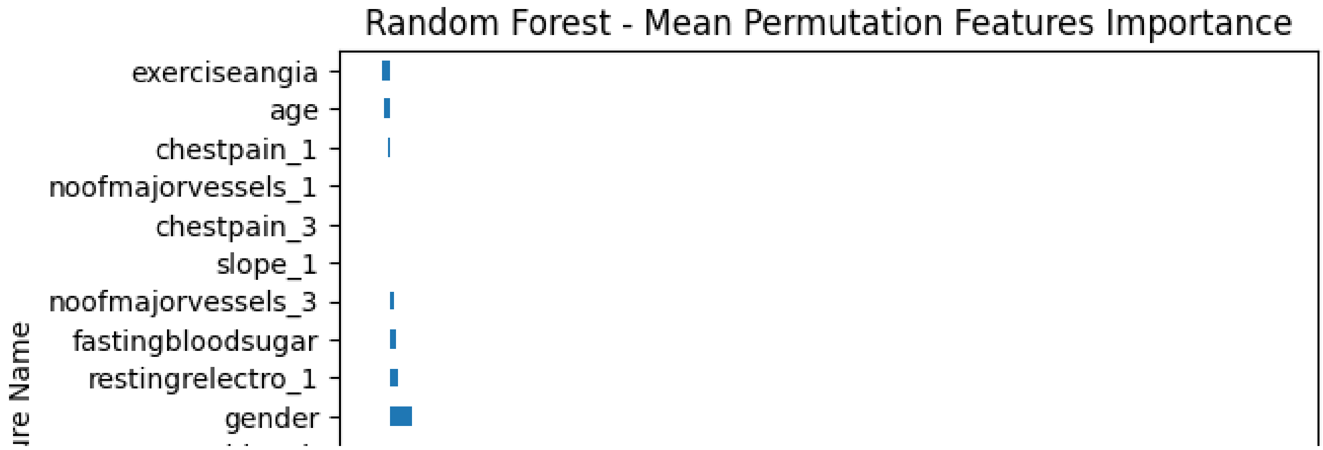
```
{'max_depth': 6, 'max_features': 'sqrt', 'max_leaf_nodes': 9, 'n_estimators': 150}
```

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
import numpy as np

# Initialize the classifier and assign it to the variable. Assign random_state 42 to ensure
india_random_forest = RandomForestClassifier(random_state=42)

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_random_forest.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_random_forest= india_random_forest.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_random_forest)*100,2)
    precision_list.append(round(precision_score(y_test_fold, target_pred_random_forest, pos_
    recall_list.append(round(recall_score(y_test_fold, target_pred_random_forest, pos_label=
    f1_list.append(round(f1_score(y_test_fold, target_pred_random_forest, pos_label=1)*100,2
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_random_forest)*100,2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_random_forest, pos_l


#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
mean_metrics = round(performance_metrics_fold.mean(),2)
```

```
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
Mean Metrics:
Accuracy       97.23
Precision      97.19
Recall         98.10
F1 Score       97.63
MCC            94.36
Specificity    96.03
dtype: float64

Standard Deviation Metrics:
Accuracy       1.65
Precision      1.96
Recall         1.83
F1 Score       1.41
MCC            3.39
Specificity    2.82
dtype: float64
```

```
#Feature Selection using Embedded Methods

#Random Forest Feature Importance Plot
from sklearn.ensemble import RandomForestClassifier
from sklearn.inspection import permutation_importance #Neccessary class for permutation impo

#Initialize the random forest classifier. Assign random_state 42 to reproduce results
random_forest_embedded = RandomForestClassifier(random_state=42)

#Fit the training data set to the random forest classifier
random_forest_embedded.fit(x_train, y_train.values.ravel()).predict(x_test)

#Calculate the feature importance based on the permutation method
random_permutation= permutation_importance(random_forest_embedded, x_test, y_test, n_repeats

#Extract feature importance plot
(pd.Series(random_permutation.importances_mean, index=x_train.columns)
   .nlargest(20)
   .plot(kind='barh'))

import matplotlib.pyplot as plt
# Add plot labels
plt.xlabel('Feature Importance')
plt.ylabel('Feature Name')
plt.title('Random Forest - Mean Permutation Features Importance')
plt.show()


#Based on feature importance plot, all features below ca_1 appear to be most relevant

#Drop least releavnt features from x_train and x_test

#Features to drop based on importance chart
features_remove = ['exerciseangia','age','chestpain_1','noofmajorvessels_1','chestpain_3','s

#Remove selected features from x_train and x_test
x_train_perm = x_train.drop(columns=features_remove)
x_test_perm = x_test.drop(columns=features_remove)
```




```
#Remove features from consistent dataset

#Modify consistent dataset for k-fold cross-validation

#Data will be scaled using the robust scaler that is less susceptible to outliers
from sklearn.preprocessing import RobustScaler

#Subset of numerical features
india_numerical =['restingBP']

#Separate target column
x_simple = data_india_coded.drop(columns=['target'] + features_remove)
y_simple = data_india_coded['target']

#Initialize RobustScaler
scaler = RobustScaler()
#Fit the consistent dataset to the RobustScaler instance.
x_simple[india_numerical] = scaler.fit_transform(x_simple[india_numerical])
```

```
#Repeat Random Forest Classifier and Output Statistics
#Initialize the random forest classifier and assign to variable india_random_forest. Assign
india_random_forest = RandomForestClassifier(random_state=42)

#Fit the training data set to the random forest classifier
india_random_forest.fit(x_train_perm, y_train.values.ravel()).predict(x_test_perm)

#Predict the presence of heart disese by inputting the test data into the india_random_fores
target_pred_random_forest = india_random_forest.predict(x_test_perm)

accuracy_random_forest =  round(accuracy_score(y_test, target_pred_random_forest),4)*100
precision_random_forest = round(precision_score(y_test, target_pred_random_forest, pos_label
recall_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=1),3)
f1_score_random_forest = round(f1_score(y_test, target_pred_random_forest, pos_label=1),3)
mcc_random_forest = round(matthews_corrcoef(y_test, target_pred_random_forest),3)
specificity_random_forest = round(recall_score(y_test, target_pred_random_forest, pos_label=

#Organize performance metrics into a list
performance_random_forest = [["Random Forest", accuracy_random_forest,specificity_random_for

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_random_forest, columns=['Model', 'Accuracy', '
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_random_forest = performance_metrics

performance_metrics
```

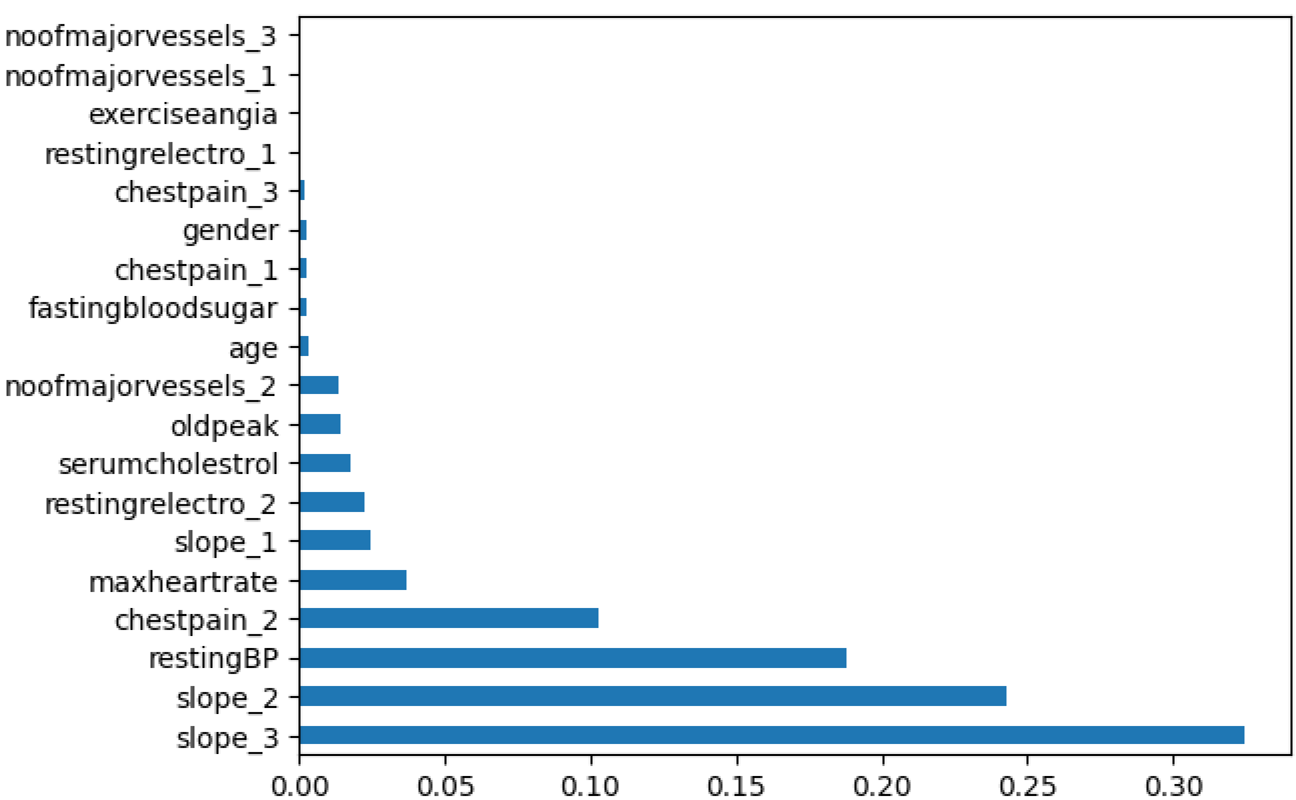
	Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
	Random Forest	86.75	0.844	0.875	0.887	0.881	0.732

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
from sklearn.tree import DecisionTreeClassifier
import numpy as np

# Initialize the classifier and assign it to the variable. Assign random_state 42 to ensure
india_random_forest = RandomForestClassifier(random_state=42)

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_random_forest.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_random_forest= india_random_forest.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_random_forest)*100,2)
    precision_list.append(round(precision_score(y_test_fold, target_pred_random_forest, pos_
    recall_list.append(round(recall_score(y_test_fold, target_pred_random_forest, pos_label=
    f1_list.append(round(f1_score(y_test_fold, target_pred_random_forest, pos_label=1)*100,2
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_random_forest)*100,2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_random_forest, pos_l


#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
```

```
mean_metrics = round(performance_metrics_fold.mean(),2)
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
Mean Metrics:
Accuracy       92.97
Precision      94.66
Recall         93.28
F1 Score       93.89
MCC            85.80
Specificity    92.54
dtype: float64

Standard Deviation Metrics:
Accuracy       2.70
Precision      3.35
Recall         3.85
F1 Score       2.39
MCC            5.43
Specificity    4.87
dtype: float64
```

```
#Feature Selection using Embedded Methods

#Gradient Boosting Feature Importance Plot
from sklearn.ensemble import GradientBoostingClassifier

#Initialize the random forest classifier. Assign random_state 42 to reproduce results
gradient_embedded =GradientBoostingClassifier(random_state=42)

#Fit the training data set to the random forest classifier
gradient_embedded.fit(x_train, y_train.values.ravel()).predict(x_test)

#Extract feature importance plot
(pd.Series(gradient_embedded.feature_importances_, index=x_train.columns)
   .nlargest(20)
   .plot(kind='barh'))

#Based on feature importance plot, all features below slope_1 appear to be most relevant

#Drop least releavnt features from x_train and x_test

#Features to drop based on importance chart
features_remove = ['noofmajorvessels_3','noofmajorvessels_1','exerciseangia','restingrelectr

#Remove selected features from x_train and x_test
x_train_embedded = x_train.drop(columns=features_remove)
x_test_embedded = x_test.drop(columns=features_remove)
```



```
#Remove features from consistent dataset

#Modify consistent dataset for k-fold cross-validation

#Data will be scaled using the robust scaler that is less susceptible to outliers
from sklearn.preprocessing import RobustScaler

#Subset of numerical features
india_numerical =[ 'restingBP','maxheartrate']

#Separate target column
x_simple = data_india_coded.drop(columns=['target'] + features_remove)
y_simple = data_india_coded['target']

#Initialize RobustScaler
scaler = RobustScaler()
#Fit the consistent dataset to the RobustScaler instance.
x_simple[india_numerical] = scaler.fit_transform(x_simple[india_numerical])
```

```
#Gradient Boosting

#Import gradient boosting classifier from scikit-learn libraries
from sklearn.ensemble import GradientBoostingClassifier

#Initialize the support vector machine classifier and assign to variable india_decision_tree
india_gradient = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0, max_depth=1

#Fit the training data set to the support vector machine classifier
india_gradient.fit(x_train_embedded, y_train.values.ravel()).predict(x_test_embedded)

#Predict the presence of heart disese by inputting the test data into the india_gradient
target_pred_gradient = india_gradient.predict(x_test_embedded)

accuracy_gradient =  round(accuracy_score(y_test, target_pred_gradient),4)*100
precision_gradient = round(precision_score(y_test, target_pred_gradient, pos_label=1),3)
recall_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=1),3)
f1_score_gradient = round(f1_score(y_test, target_pred_gradient, pos_label=1),3)
mcc_gradient = round(matthews_corrcoef(y_test, target_pred_gradient),3)
specificity_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=0),3)

#Organize performance metrics into a list
performance_gradient = [["Gradient Boosting", accuracy_gradient,specificity_gradient,precisi

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_gradient, columns=['Model', 'Accuracy','Specif
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_gradient = performance_metrics

performance_metrics
```

	Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
	Gradient Boosting	92.25	0.899	0.92	0.941	0.931	0.843

```
#Gradient Boosting

#Initialize the gradient boosting classifier and assign to variable india_gradient. Assign r
india_gradient = GradientBoostingClassifier(random_state=42)

#A parameter grid was created using selected integers to cycle through in order to optimize
#These features were selected based on the values available in the sklearn documentation
param_dist = {'n_estimators': [50, 100, 200],
              'learning_rate': [0.01, 0.1, 0.2],
              'max_depth': [3, 4, 5],
              'min_samples_split': [2, 5, 10],
              'min_samples_leaf': [1, 2, 4]}

#Fit the training data set to the support vector machine classifier
india_gradient.fit(x_train, y_train.values.ravel()).predict(x_test)

#Initialize the GridSearchCV class using the gradient boosting, the parameter grid and a 10-
grid_india_gb = GridSearchCV(india_gradient, param_dist, cv=10)
grid_india_gb.fit(x_train_embedded, y_train.values.ravel())

#Output the best parameters, the model is optimized based on accuracy score
best_params_gb = grid_india_gb.best_params_
print(best_params_gb)

#Fit the model using athe best parameters
india_gradient= GradientBoostingClassifier(**best_params_gb, random_state=42)
india_gradient.fit(x_train_embedded, y_train.values.ravel())

#Predict the presence of heart disese by inputting the test data into the india_gradient
target_pred_gradient = india_gradient.predict(x_test_embedded)

accuracy_gradient =  round(accuracy_score(y_test, target_pred_gradient),4)*100
precision_gradient = round(precision_score(y_test, target_pred_gradient, pos_label=1),3)
recall_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=1),3)
f1_score_gradient = round(f1_score(y_test, target_pred_gradient, pos_label=1),3)
mcc_gradient = round(matthews_corrcoef(y_test, target_pred_gradient),3)
specificity_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=0),3)

#Organize performance metrics into a list
performance_gradient = [["Gradient Boosting", accuracy_gradient,specificity_gradient,precisi

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_gradient, columns=['Model', 'Accuracy','Specif
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_gradient = performance_metrics

performance_metrics
```

```
{'learning_rate': 0.1, 'max_depth': 3, 'min_samples_leaf': 1, 'min_samples_split': 10, '
```

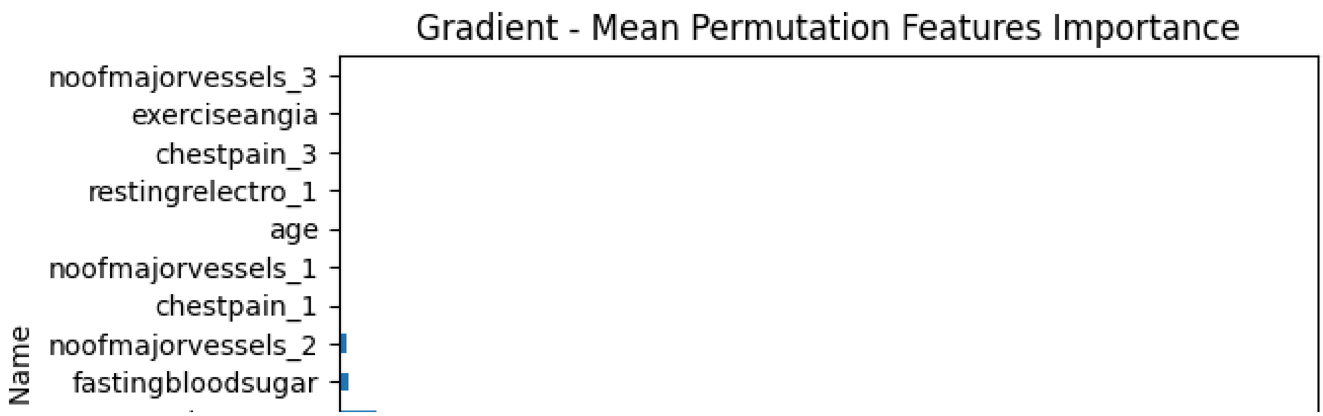
Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
Gradient Boosting	93.0	0.911	0.929	0.946	0.937	0.858

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
from sklearn.ensemble import GradientBoostingClassifier
import numpy as np

#Initialize the classifier and assign to variable. Assign random_state 0 to reproduce result
india_gradient = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0, max_depth=1

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_gradient.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_gradient= india_gradient.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_gradient)*100,2))
    precision_list.append(round(precision_score(y_test_fold, target_pred_gradient, pos_label
    recall_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=1)*10
    f1_list.append(round(f1_score(y_test_fold, target_pred_gradient, pos_label=1)*100,2))
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_gradient)*100,2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=

#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
mean_metrics = round(performance_metrics_fold.mean(),2)
```

```
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
Mean Metrics:
Accuracy       93.27
Precision      94.34
Recall         94.14
F1 Score       94.19
MCC            86.30
Specificity    92.07
dtype: float64

Standard Deviation Metrics:
Accuracy       2.03
Precision      2.70
Recall         2.85
F1 Score       1.76
MCC            4.14
Specificity    4.07
dtype: float64
```

```
#Feature Selection using Embedded Methods

#Gradient Boosting Feature Importance Plot
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.inspection import permutation_importance #Neccessary class for permutation impo

#Initialize the random forest classifier. Assign random_state 42 to reproduce results
gradient_embedded =GradientBoostingClassifier(random_state=42)

#Fit the training data set to the random forest classifier
gradient_embedded.fit(x_train, y_train.values.ravel()).predict(x_test)

#Calculate the feature importance based on the permutation method
gradient_permutation= permutation_importance(gradient_embedded, x_test, y_test, n_repeats=10

#Extract feature importance plot
(pd.Series(gradient_permutation.importances_mean, index=x_train.columns)
   .nlargest(20)
   .plot(kind='barh'))

import matplotlib.pyplot as plt
# Add plot labels
plt.xlabel('Feature Importance')
plt.ylabel('Feature Name')
plt.title('Gradient - Mean Permutation Features Importance')
plt.show()

#Based on feature importance plot, all features below ca_1 appear to be most relevant

#Drop least releavnt features from x_train and x_test

#Features to drop based on importance chart
features_remove = ['noofmajorvessels_3','exerciseangia','chestpain_3','restingrelectro_1','a

#Remove selected features from x_train and x_test
x_train_perm = x_train.drop(columns=features_remove)
x_test_perm = x_test.drop(columns=features_remove)
```




```
#Remove features from consistent dataset

#Modify consistent dataset for k-fold cross-validation

#Data will be scaled using the robust scaler that is less susceptible to outliers
from sklearn.preprocessing import RobustScaler

#Subset of numerical features
india_numerical =['restingBP', 'oldpeak']

#Separate target column
x_simple = data_india_coded.drop(columns=['target'] + features_remove)
y_simple = data_india_coded['target']

#Initialize RobustScaler
scaler = RobustScaler()
#Fit the consistent dataset to the RobustScaler instance.
x_simple[india_numerical] = scaler.fit_transform(x_simple[india_numerical])
```

```
#Gradient Boosting

#Import gradient boosting classifier from scikit-learn libraries
from sklearn.ensemble import GradientBoostingClassifier

#Initialize the support vector machine classifier and assign to variable india_decision_tree
india_gradient = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0, max_depth=1

#Fit the training data set to the support vector machine classifier
india_gradient.fit(x_train_perm, y_train.values.ravel()).predict(x_test_perm)

#Predict the presence of heart disese by inputting the test data into the india_gradient
target_pred_gradient = india_gradient.predict(x_test_perm)

accuracy_gradient =  round(accuracy_score(y_test, target_pred_gradient),4)*100
precision_gradient = round(precision_score(y_test, target_pred_gradient, pos_label=1),3)
recall_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=1),3)
f1_score_gradient = round(f1_score(y_test, target_pred_gradient, pos_label=1),3)
mcc_gradient = round(matthews_corrcoef(y_test, target_pred_gradient),3)
specificity_gradient = round(recall_score(y_test, target_pred_gradient, pos_label=0),3)

#Organize performance metrics into a list
performance_gradient = [["Gradient Boosting", accuracy_gradient,specificity_gradient,precisi

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_gradient, columns=['Model', 'Accuracy','Specif
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_gradient = performance_metrics

performance_metrics
```

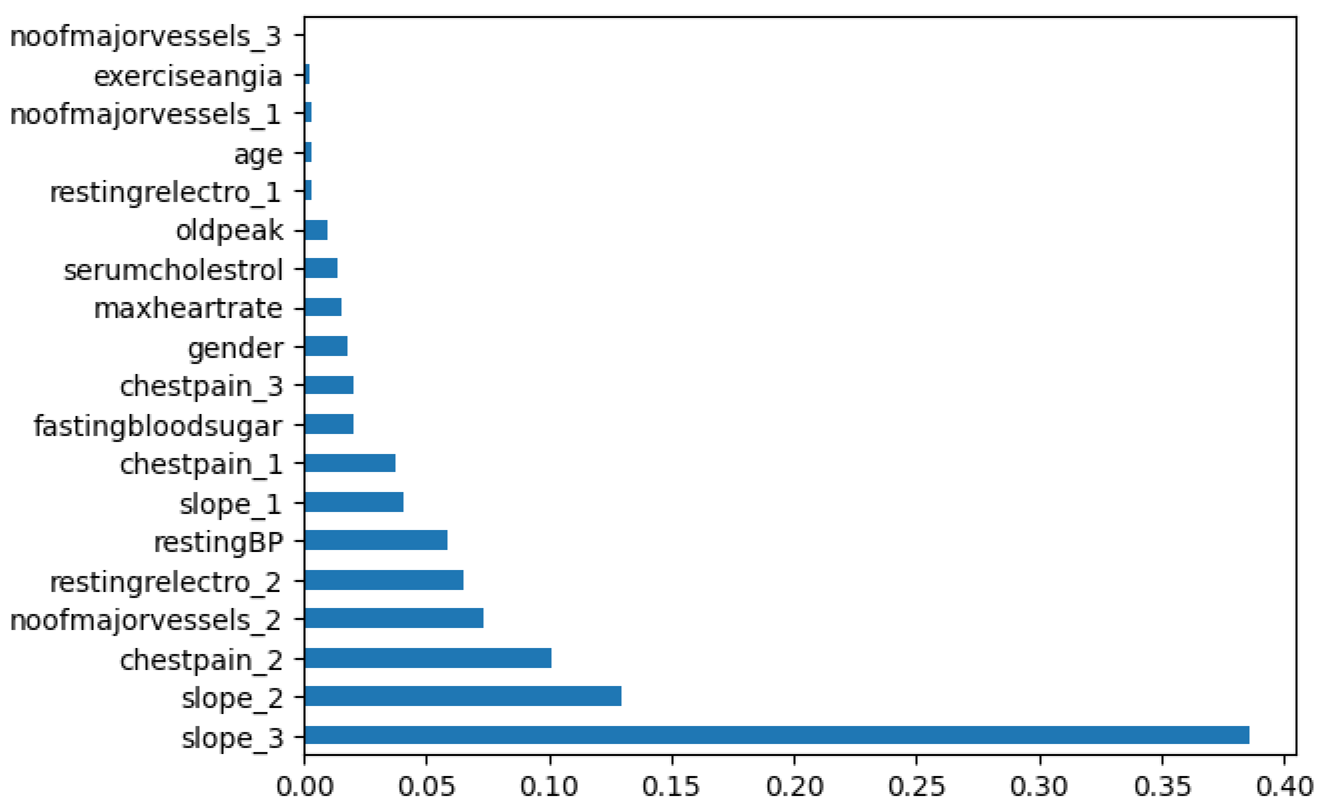
	Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
	Gradient Boosting	94.75	0.922	0.939	0.968	0.953	0.894

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
from sklearn.ensemble import GradientBoostingClassifier
import numpy as np

#Initialize the classifier and assign to variable. Assign random_state 0 to reproduce result
india_gradient = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0, max_depth=1

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_gradient.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_gradient= india_gradient.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_gradient)*100,2))
    precision_list.append(round(precision_score(y_test_fold, target_pred_gradient, pos_label
    recall_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=1)*10
    f1_list.append(round(f1_score(y_test_fold, target_pred_gradient, pos_label=1)*100,2))
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_gradient)*100,2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=

#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
mean_metrics = round(performance_metrics_fold.mean(),2)
```

```
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
Mean Metrics:
Accuracy       95.20
Precision      95.81
Recall         95.98
F1 Score       95.87
MCC            90.20
Specificity    94.13
dtype: float64

Standard Deviation Metrics:
Accuracy       2.09
Precision      2.41
Recall         2.28
F1 Score       1.80
MCC            4.29
Specificity    3.46
dtype: float64
```

```
#Feature Selection using Embedded Methods

#XGBoost Feature Importance Plot
import xgboost as xgb

#Initialize the random forest classifier. Assign random_state 42 to reproduce results
xgboost_embedded =xgb.XGBClassifier(n_estimators=100, objective='binary:logistic', tree_meth

#Fit the training data set to the random forest classifier
xgboost_embedded.fit(x_train, y_train.values.ravel()).predict(x_test)

#Extract feature importance plot
(pd.Series(xgboost_embedded.feature_importances_, index=x_train.columns)
   .nlargest(20)
   .plot(kind='barh'))

#Based on feature importance plot, all features below slope_1 appear to be most relevant

#Drop least releavnt features from x_train and x_test

#Features to drop based on importance chart
features_remove = ['noofmajorvessels_3','exerciseangia','noofmajorvessels_1','age','restingr

#Remove selected features from x_train and x_test
x_train_embedded = x_train.drop(columns=features_remove)
x_test_embedded = x_test.drop(columns=features_remove)
```



```
#Remove features from consistent dataset

#Modify consistent dataset for k-fold cross-validation

#Data will be scaled using the robust scaler that is less susceptible to outliers
from sklearn.preprocessing import RobustScaler

#Subset of numerical features
india_numerical =[ 'restingBP']

#Separate target column
x_simple = data_india_coded.drop(columns=['target'] + features_remove)
y_simple = data_india_coded['target']

#Initialize RobustScaler
scaler = RobustScaler()
#Fit the consistent dataset to the RobustScaler instance.
x_simple[india_numerical] = scaler.fit_transform(x_simple[india_numerical])
```

```
#XGBoost

#Import xgboost
import xgboost as xgb

#Initialize the support vector machine classifier and assign to variable india_decision_tree
india_xgb = xgb.XGBClassifier(n_estimators=100, objective='binary:logistic', tree_method='hi

#Fit the training data set to the support vector machine classifier
india_xgb.fit(x_train_embedded, y_train.values.ravel()).predict(x_test_embedded)

#Predict the presence of heart disese by inputting the test data into the india_xgb
target_pred_xgb = india_xgb.predict(x_test_embedded)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score

accuracy_xgb =  round(accuracy_score(y_test, target_pred_xgb),4)*100
precision_xgb = round(precision_score(y_test, target_pred_xgb, pos_label=1),3)
recall_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=1),3)
f1_score_xgb = round(f1_score(y_test, target_pred_xgb, pos_label=1),3)
mcc_xgb = round(matthews_corrcoef(y_test, target_pred_xgb),3)
specificity_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=0),3)

#Organize performance metrics into a list
performance_xgb = [["XGBoost", accuracy_xgb,specificity_xgb,precision_xgb,recall_xgb,f1_scor

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_xgb, columns=['Model', 'Accuracy','Specificity
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_xgb= performance_metrics

performance_metrics
```

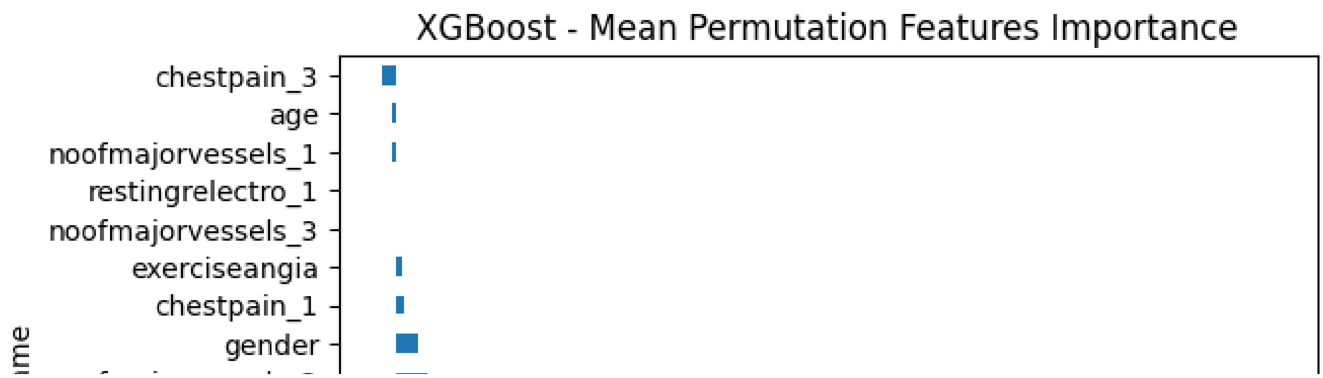
Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
XGBoost	94.0	0.916	0.934	0.959	0.946	0.879

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
import xgboost as xgb
import numpy as np

#Initialize the classifier and assign to variable india_decision_tree. Assign random_state 0
india_xgb = xgb.XGBClassifier(n_estimators=100, objective='binary:logistic', tree_method='hi

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_gradient.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_gradient= india_gradient.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_gradient)*100,2))
    precision_list.append(round(precision_score(y_test_fold, target_pred_gradient, pos_label
    recall_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=1)*10
    f1_list.append(round(f1_score(y_test_fold, target_pred_gradient, pos_label=1)*100,2))
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_gradient)*100,2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=

#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
mean_metrics = round(performance_metrics_fold.mean(),2)
```

```
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
Mean Metrics:
Accuracy       95.30
Precision      95.52
Recall         96.50
F1 Score       95.98
MCC            90.42
Specificity    93.65
dtype: float64

Standard Deviation Metrics:
Accuracy       2.07
Precision      2.60
Recall         2.33
F1 Score       1.76
MCC            4.25
Specificity    3.82
dtype: float64
```

```
#Feature Selection using Embedded Methods

#XGBoost Feature Importance Plot
import xgboost as xgb

#Initialize the random forest classifier. Assign random_state 42 to reproduce results
xgboost_embedded =xgb.XGBClassifier(n_estimators=100, objective='binary:logistic', tree_meth

#Fit the training data set to the random forest classifier
xgboost_embedded.fit(x_train, y_train.values.ravel()).predict(x_test)

#Calculate the feature importance based on the permutation method
xgboost_permutation= permutation_importance(xgboost_embedded, x_test, y_test, n_repeats=10,

#Extract feature importance plot
(pd.Series(xgboost_permutation.importances_mean, index=x_train.columns)
   .nlargest(20)
   .plot(kind='barh'))

import matplotlib.pyplot as plt
# Add plot labels
plt.xlabel('Feature Importance')
plt.ylabel('Feature Name')
plt.title('XGBoost - Mean Permutation Features Importance')
plt.show()

#Based on feature importance plot, all features below ca_1 appear to be most relevant

#Drop least relevant features from x_train and x_test

#Features to drop based on importance chart
features_remove = ['exerciseangia','age','chestpain_1','noofmajorvessels_1','chestpain_3','s

#Remove selected features from x_train and x_test
x_train_perm = x_train.drop(columns=features_remove)
x_test_perm = x_test.drop(columns=features_remove)
```




```
#Remove features from consistent dataset

#Modify consistent dataset for k-fold cross-validation

#Data will be scaled using the robust scaler that is less susceptible to outliers
from sklearn.preprocessing import RobustScaler

#Subset of numerical features
india_numerical =['restingBP']

#Separate target column
x_simple = data_india_coded.drop(columns=['target'] + features_remove)
y_simple = data_india_coded['target']

#Initialize RobustScaler
scaler = RobustScaler()
#Fit the consistent dataset to the RobustScaler instance.
x_simple[india_numerical] = scaler.fit_transform(x_simple[india_numerical])
```

```
#XGBoost

#Import xgboost
import xgboost as xgb

#Initialize the support vector machine classifier and assign to variable india_decision_tree
india_xgb = xgb.XGBClassifier(n_estimators=100, objective='binary:logistic', tree_method='hi

#Fit the training data set to the support vector machine classifier
india_xgb.fit(x_train_perm, y_train.values.ravel()).predict(x_test_perm)

#Predict the presence of heart disese by inputting the test data into the india_xgb
target_pred_xgb = india_xgb.predict(x_test_perm)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score

accuracy_xgb =  round(accuracy_score(y_test, target_pred_xgb),4)*100
precision_xgb = round(precision_score(y_test, target_pred_xgb, pos_label=1),3)
recall_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=1),3)
f1_score_xgb = round(f1_score(y_test, target_pred_xgb, pos_label=1),3)
mcc_xgb = round(matthews_corrcoef(y_test, target_pred_xgb),3)
specificity_xgb = round(recall_score(y_test, target_pred_xgb, pos_label=0),3)

#Organize performance metrics into a list
performance_xgb = [["XGBoost", accuracy_xgb,specificity_xgb,precision_xgb,recall_xgb,f1_scor

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_xgb, columns=['Model', 'Accuracy','Specificity
performance_metrics.index = [""]

#Create copy to append to a summary table
st1_pm_xgb= performance_metrics

performance_metrics
```

Model	Accuracy	Specificity	Precision	Recall	F1 Score	MCC
XGBoost	95.75	0.944	0.955	0.968	0.962	0.914

```
from sklearn.model_selection import cross_val_score, RepeatedStratifiedKFold
import xgboost as xgb
import numpy as np

#Initialize the classifier and assign to variable india_decision_tree. Assign random_state 0
india_xgb = xgb.XGBClassifier(n_estimators=100, objective='binary:logistic', tree_method='hi

# Initialize RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

#Create empty lists to store performance metrics
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
mcc_list = []
specificity_list = []

#We will begin by iterating through the folds created by the Stratified K-fold
for train_index, test_index in cv.split(x_simple, y_simple.values.ravel()):
    #Start by grouping training and testing features based on training and testing row indic
    x_train_fold, x_test_fold = x_simple.iloc[train_index], x_simple.iloc[test_index]
    #Group labels based on training and testing row indices within the fold
    y_train_fold, y_test_fold = y_simple.iloc[train_index], y_simple.iloc[test_index]

    #Fit the training data set to the classifier
    india_gradient.fit(x_train_fold, y_train_fold.values.ravel())

    #Predict the presence of heart disease by inputting the test data
    target_pred_gradient= india_gradient.predict(x_test_fold)

    #Calculate performance metrics for the current fold
    accuracy_list.append(round(accuracy_score(y_test_fold, target_pred_gradient)*100,2))
    precision_list.append(round(precision_score(y_test_fold, target_pred_gradient, pos_label
    recall_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=1),2)
    f1_list.append(round(f1_score(y_test_fold, target_pred_gradient, pos_label=1),2))
    mcc_list.append(round(matthews_corrcoef(y_test_fold, target_pred_gradient),2))
    specificity_list.append(round(recall_score(y_test_fold, target_pred_gradient, pos_label=

#Create a DataFrame to store metrics for each fold and repeat
performance_metrics_fold = pd.DataFrame({
    'Accuracy': accuracy_list,
    'Precision': precision_list,
    'Recall': recall_list,
    'F1 Score': f1_list,
    'MCC': mcc_list,
    'Specificity': specificity_list
})

#Calculate mean and standard deviation across folds and repeats
mean_metrics = round(performance_metrics_fold.mean(),2)
```

```
std_metrics = round(performance_metrics_fold.std(),2)

#Display mean and standard deviation
print('Mean Metrics:')
print(mean_metrics)
print('\nStandard Deviation Metrics:')
print(std_metrics)

#performance_metrics_fold
```

```
Mean Metrics:
Accuracy       95.20
Precision       0.96
Recall          0.96
F1 Score        0.96
MCC             0.90
Specificity     0.94
dtype: float64

Standard Deviation Metrics:
Accuracy       2.09
Precision      0.02
Recall         0.02
F1 Score       0.02
MCC            0.04
Specificity    0.04
dtype: float64
```

Wrapper Methods of Feature Selection: Backwards Elimination

```
pip install mlxtend
```

```
Requirement already satisfied: mlxtend in /usr/local/lib/python3.10/dist-packages (0.22.
Requirement already satisfied: scipy>=1.2.1 in /usr/local/lib/python3.10/dist-packages (
Requirement already satisfied: numpy>=1.16.2 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: pandas>=0.24.2 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: scikit-learn>=1.0.2 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: matplotlib>=3.0.0 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: joblib>=0.13.2 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (fr
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from
```

Backward Elimination: Decision Tree Classifier

```
#Import sequential feature selector class from mlxtend.feature_selection library
from mlxtend.feature_selection import SequentialFeatureSelector as SFS

#Instantiate decision tree classifier and set random state to ensure reproducibility of the
decision_backward =DecisionTreeClassifier(random_state = 42)

#Instantiate backward elimination feature selection
backward_elim = SFS(estimator=decision_backward,
           k_features=(1, 19), #Indicate that any number of features between 0 and 20 may be
           forward=False,
           floating=False,
           scoring='accuracy', #Metric to maximized
           cv=5) #5-fold cross-validation to be used during feature selection

#Fit backward elimination feature selection using the training data
backward_elim = backward_elim.fit(x_train, y_train)

#Access average accuracy scores and feature names
results = pd.DataFrame.from_dict(backward_elim.get_metric_dict()).T
print(results[['avg_score', 'feature_names']])

#Identify the maximum average score calculate and print the corresponding feature indices
max_features = results[results['avg_score'] == results['avg_score'].max()]
print(max_features['feature_idx'].values[0])
print(max_features['feature_names'].values[0])
```

```
     avg_score                                      feature_names
19  0.936667  (age, gender, restingBP, serumcholestrol, fast...
18      0.95  (age, gender, restingBP, serumcholestrol, maxh...
17  0.951667  (gender, restingBP, serumcholestrol, maxheartr...
16  0.956667  (gender, restingBP, serumcholestrol, maxheartr...
15  0.953333  (gender, restingBP, serumcholestrol, maxheartr...
14  0.953333  (gender, restingBP, serumcholestrol, maxheartr...
13     0.955  (restingBP, serumcholestrol, maxheartrate, exe...
12  0.956667  (restingBP, maxheartrate, exerciseangia, oldpe...
11  0.953333  (restingBP, maxheartrate, oldpeak, chestpain_1...
10  0.951667  (restingBP, maxheartrate, oldpeak, chestpain_1...
9   0.953333  (restingBP, maxheartrate, oldpeak, chestpain_1...
8   0.953333  (restingBP, maxheartrate, oldpeak, chestpain_1...
7       0.95  (restingBP, maxheartrate, oldpeak, chestpain_1...
6   0.951667  (restingBP, maxheartrate, oldpeak, chestpain_2...
5      0.945  (restingBP, maxheartrate, chestpain_2, slope_2...
4   0.921667         (restingBP, chestpain_2, slope_2, slope_3)
3   0.913333                      (restingBP, slope_2, slope_3)
2   0.916667                                 (slope_2, slope_3)
1      0.715                                         (slope_2,)
(1, 2, 3, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18)
('gender', 'restingBP', 'serumcholestrol', 'maxheartrate', 'exerciseangia', 'oldpeak', '
```

```
#Select columns from x_train and x_test identified by backward elimination
selected_features = list(max_features['feature_idx'].values[0])
x_train_backward = x_train.iloc[:,selected_features]
x_test_backward = x_test.iloc[:,selected_features]


#Modify consistent dataset for k-fold cross-validation

#Features to drop based on simple filters
features_select= list(max_features['feature_names'].values[0])

#Data will be scaled using the robust scaler that is less susceptible to outliers
from sklearn.preprocessing import RobustScaler

#Subset of numerical features
india_numerical =['restingBP', 'serumcholestrol', 'maxheartrate', 'oldpeak']

#Initialize RobustScaler
scaler = RobustScaler()

#Initialize RobustScaler
scaler = RobustScaler()

#Separate target column
x_backward = data_india_coded.drop(columns=['target'])
y_backward = data_india_coded['target']

#Choose variables
x_backward = x_backward[x_backward.columns.intersection(features_select)]

#Fit the consistent dataset to the RobustScaler instance.
x_backward[india_numerical] = scaler.fit_transform(x_backward[india_numerical])

x_backward.head()
```

	gender	restingBP	serumcholestrol	maxheartrate	exerciseangia	oldpeak	chestpain_
0	1	0.461538	-1.887240	0.018100	0	1.035714	(
1	1	-1.019231	-0.528190	-0.561086	0	0.464286	(
2	1	-0.269231	-1.044510	1.013575	1	0.928571	(
3	1	-0.173077	-0.136499	0.126697	0	0.285714	(
4	1	1.000000	-1.887240	-0.180995	0	1.035714	

```
#Decision Tree

from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier

#Import classes to calculate memory consumption and runtime
import timeit
import psutil

#Initialize the decision tree classifier and assign to variable india_decision_tree. Assign
india_decision_tree = DecisionTreeClassifier(random_state=42)

#Begin timing of fitting and prediction process
start_time = timeit.default_timer()

#Fit the training data set to the decision tree model
india_decision_tree.fit(x_train_backward, y_train.values.ravel()).predict(x_test_backward)

#Predict the presence of heart disese by inputting the test data into the india_decision_tre
target_pred_decision_tree = india_decision_tree.predict(x_test_backward)

#Stop timing of fitting and prediction process
end_time = timeit.default_timer()

#Calculate total time
computational_time = end_time - start_time
#Calculate memory usage in megabytes
memory_usage = round(psutil.Process().memory_info().rss/ (1024 * 1024),2)

from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score, matthew

accuracy_decision_tree =  round(accuracy_score(y_test, target_pred_decision_tree),4)*100
precision_decision_tree = round(precision_score(y_test, target_pred_decision_tree, pos_label
recall_decision_tree = round(recall_score(y_test, target_pred_decision_tree, pos_label=1),3)
f1_score_decision_tree = round(f1_score(y_test, target_pred_decision_tree, pos_label=1),3)
mcc_decision_tree = round(matthews_corrcoef(y_test, target_pred_decision_tree),3)
specificity_decision_tree = round(recall_score(y_test, target_pred_decision_tree, pos_label=

#Organize performance metrics into a list
performance_decision_tree = [["Decision Tree", accuracy_decision_tree, specificity_decision_

#Create dataframe of performance metrics
performance_metrics= pd.DataFrame(performance_decision_tree, columns=['Model', 'Accuracy', '
```