# Heart Disease Prediction:

## Abstract:

This is a project on heart disease prediction with machine learning algorithms. By utilizing such an ample dataset, the study is intended to find significant risk factors and develop a precise classification scheme for early diagnosis. The method is based on substantial data preprocessing (including outliers deletion) and assessing of different machine learning models such as Logistic Regression, Decision Tree, Random Forest, SVM, KNN, Gradient Boosting and XGBoost. The main intention with this is to obtain a good predictive accuracy and to provide then a useful tool for medical staff, in order to identify patients in danger of getting heart disease.

## Introduction:

Heart disease continues to be one of the major causes of death globally; hence reliable, and early diagnosis tools are required. This vital need is the focus of this project, attempting the prediction of heart disease using machine learning techniques. The aim is to develop an accurately predictive model to analyse patient features and give insights about their cardiac health status. By providing automatic predictions, this project aims to increase the efficiency of diagnosis, reduce human mistakes and 'save lives' by combating delay towards interventions. This paper describes how the template is built, the data collection, feature extraction and preprocessing, as well as how the model is trained, tested and refine in the future.

## Dataset Description:

The data set used in this project (1190 × 12) gives a rich source of information for the prediction of heart disease. Important real-valued features are ‘age’, ‘sex’, ‘chest pain type’, ‘resting bp s’ (resting blood pressure), ‘cholesterol’, ‘fasting blood sugar’, ‘resting ecg’ (resting electrocardiographic results), ‘max heart rate’ (maximum heart rate achieved), ‘exercise angina’ (exercise induced angina), ‘oldpeak’ (ST depression induced by exercise relative to rest) and ‘ST slope’ (the slope of the peak exercise ST segment). The ‘target’ variable is a 1 if there is heart disease, 0 otherwise. Given this comprehensive dataset, a detailed exploration of a wide range of physiological and clinical parameters relating to the health of the heart is possible.

## Technologies and Libraries Used:

The project is written in Python and relies on the extensive list of libraries for data science and machine learning. Pandas is commonly used for data manipulation/exploration and this makes for efficient dataset management. It is being used for numerical computation with array computing capability. The scikit-learn is a library and collection of toolboxes that endows the machine learning algorithm pipeline with several implementations including LogisticRegression, DecisionTreeClassifier, RandomForestClassifier, SVC (Support Vector Machine), KNeighborsClassifier and GradientBoostingClassifier. The reasoning for using XGBoost is due to its high accuracy in classification. Results and performance comparisons are visualized using Matplotlib and Seaborn to demonstrate the importance of the results shown. scipy. stats itself employ for statistical analysis for instance it is used for outlier detection.

## Data Preprocessing:

As the prediction model's quality and reliability are of a great concern, data preprocessing is of vital interest here. First of all, I examined the data to see if there were any null values, and there wasn't, so don't need to perform any imputation. No normalisation is adopted as data's do not yield very high numbers. Preprocessing For the preprocessing I was mostly interested in the outlier detection and removing of the outliers, more for the numerical columns 'resting bp s', 'cholesterol', 'max heart rate' and 'oldpeak'. Interquartile range method was performed on these columns, which lead to a great amount of data reduced from 1190 to 952 values, resulting in an amelioration of data quality. Numerical features were subsequently scaled by StandardScaler to standardize their range, and followed by splitting the dataset into training and testing sets.

## Model Architecture:

This work studies several supervised machine learning classification techniques, which provide different ways for designing the architecture model.

1. Logistic Regression: A linear model developed for binary classification by way of probabilistic outcomes.
2. Decision Tree Classifier: A decision tree is a tree-like model that allows decisions to be made based on the values of the features and is able to represent non-linear relationships.

3. Random Forest Classifier: A method that constructs multiple decision trees and combines their outputs to produce more accurate and reliable predictions.
4. Support Vector Machine (SVM): SVM is a more complex model that finds the optimal hyperplane which best divides a dataset into different classes in a high-dimensional feature space.
5. K nearest neighbors (KNN): A non-parametric instance-based learning algorithm that makes use of the majority class of the k nearest neighbors of each data point to classify the data points.
6. Gradient Boosting Classifier: Another ensemble method to construct trees sequentially while each new tree compensates for errors of its predecessors.
7. XGBoost Classifier: An efficient and scalable implementation of gradient boosted decision trees known for its superior performance, which has high predictive power.

## Training Configuration:

During training, we divided the pre-processed dataset into train and test sets in ratio 80–20 with random_state=42 (for a reproducible results), stratify=y (to maintain the distribution of class). For numerical features, we used StandardScaler, and fit on training data and transform on test data (to avoid data leakage). Each model was trained with default parameters, except for LogisticRegression (solver='liblinear') and RandomForestClassifier (n_estimators=100), XGBoost (objective='binary: logistic', eval_metric='logloss', use_label_encoder=False, n_estimators=100, learning_rate=0.1). Parameter tuning for XGBoost was done by GridSearchCV with an extensive grid on n_estimators, learning_rate, max_depth, subsample, colsample_bytree, and gamma including 5-fold cross-validation.

## Results and Evaluation:

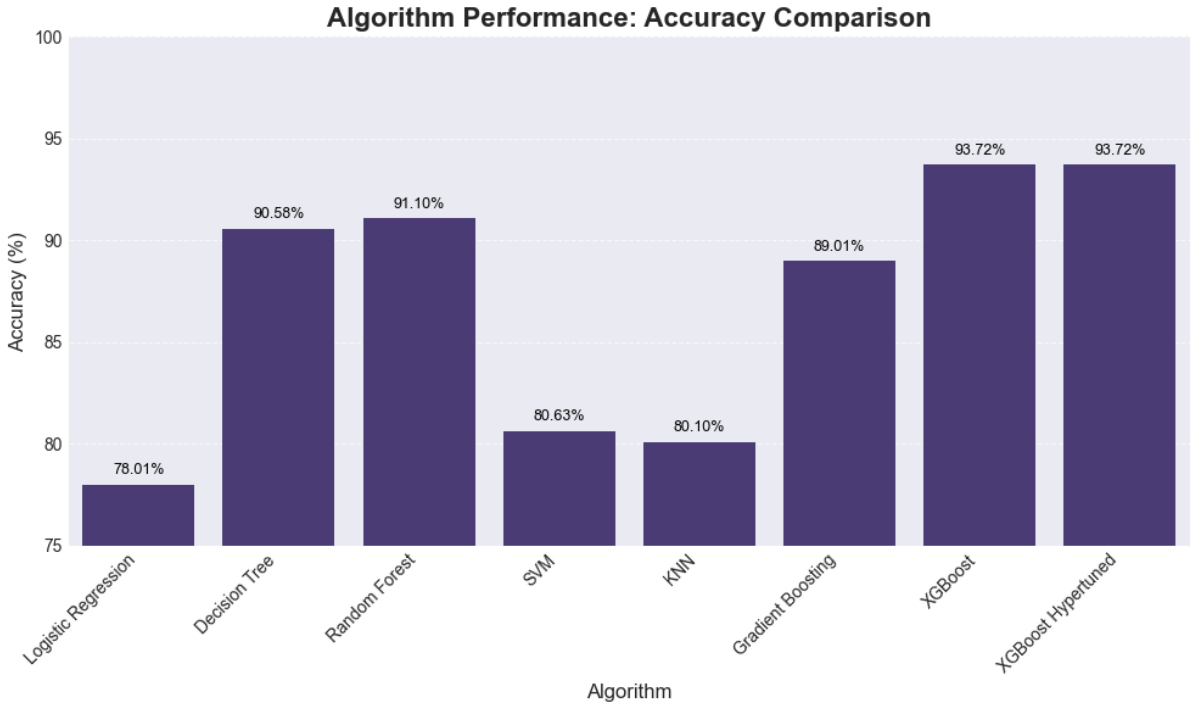
The accuracy, precision, recall, F1-score in the classification report was used to evaluate the performance of each of the algorithms.

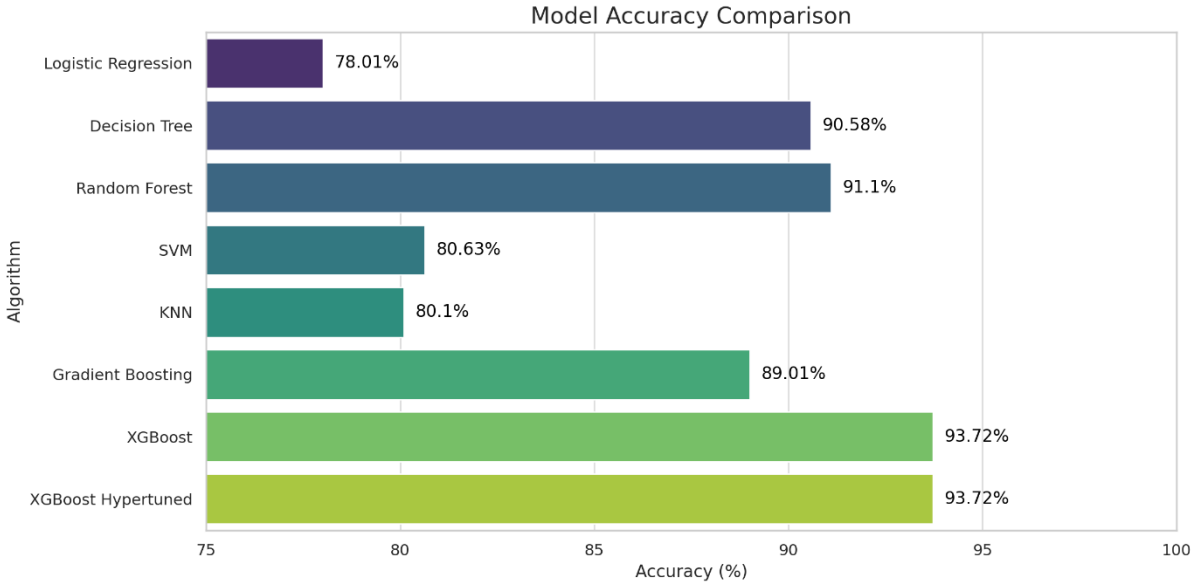
| Algorithm | Accuracy |
|---|---|
| Logistic Regression | 78.01% |
| Decision Tree | 90.58% |
| Random Forest | 91.1% |
| SVM | 80.63% |
| KNN | 80.1% |
| Gradient Boosting | 89.01% |

| | |
|---|---|
| XGBoost | 93.72% |
| XGBoost Hypertuned | 93.72% |

Many classifiers provided an accuracy of above 90%, and XGBoost consistently outperformed the others with the best accuracy rate of 93.72% both with and without hyperparameter tuning, illustrating its superior performance on this dataset. The classification reports additionally certified the chiselled together performances of the best models on various metrics.

## Results Graph:




## Challenges Faced:

It was not without challenges. A significant issue was that the dataset could be, for example, perturbed by the outlier. The IQR was effective but it ignored a portion of data that could potentially impact the generalization of the model, if not dealt consciously. There was also the question of which ML model you'd go with, among myriad others. This called for systematic comparisons and testing over several models. Hyperparameters tuning, especially in complex machine learning models like XGBoost, had spent a lot of computation cost and time to effectively explore a large search space. Keeping results reproducible across runs was also an evolving process, guided by turning components of the results into randomstates.

## Future Scope:

The work is easily extendable to several other directions. The second one is discovering high-level feature engineering methods to extract new and informative features from the original dataset, thereby improving the accuracy of models. Including more data from other sources may increase the robustness and generality of the model to other patient populations. Trying deeper learning structures such as CNN (Convolutional Neural Network) or RNN (Recurrent Neural Network) can further bring prediction power. Additionally, by porting the model to user-oriented web-based application, the model could be easily available for the healthcare professionals to make real time prediction and for the clinical decision support.

## Conclusions:

Good! That was the world's largest effort to construct and test many different machine-learning models for predicting heart disease. Careful preprocessing of the data, i.e. outlier removal, was essential for improving the data quality. The XGBoost had the highest accuracy of 93.72% in detecting diagnostic algorithm which compared to others was found to be superior. Such high accuracy suggests that machine learning could aid in the recognition and treatment of heart disease. Despite the existence of outliers and the necessity for hyperparameter tuning, the project represents a solid foundation for investigations to build upon. It is anticipated that much higher performance can be anticipated in feature engineering, data sources other than HSRC+DEG and deep learning models because the AI in healthcare is an immensely promising trend.

```
import pandas as pd
import numpy as np

df = pd.read_csv(r"C:\Users\tanis\Downloads\Projects-20240722T093004Z-001\Projects\heart_disease\Heart Disease\dataset.csv")

df.head()
```

```
   age  sex  chest pain type  resting bp s  cholesterol  fasting blood sugar  \
0   40    1                2           140          289                    0
1   49    0                3           160          180                    0
2   37    1                2           130          283                    0
3   48    0                4           138          214                    0
4   54    1                3           150          195                    0

   resting ecg  max heart rate  exercise angina  oldpeak  ST slope  target
0            0             172                0      0.0         1       0
1            0             156                0      1.0         2       1
2            1              98                0      0.0         1       0
3            0             108                1      1.5         2       1
4            0             122                0      0.0         1       0
```

```
df.shape
```

```
(1190, 12)
```

```
df.describe()
```

```
               age          sex  chest pain type  resting bp s  cholesterol  \
count  1190.000000  1190.000000      1190.000000   1190.000000  1190.000000
mean     53.720168     0.763866         3.232773    132.153782   210.363866
std       9.358203     0.424884         0.935480     18.368823   101.420489
min      28.000000     0.000000         1.000000      0.000000     0.000000
25%      47.000000     1.000000         3.000000    120.000000
```

```
188.000000
50%      54.000000     1.000000         4.000000    130.000000
229.000000
75%      60.000000     1.000000         4.000000    140.000000
269.750000
max      77.000000     1.000000         4.000000    200.000000
603.000000

       fasting blood sugar  resting ecg  max heart rate  exercise
angina  \
count          1190.000000  1190.000000     1190.000000
1190.000000
mean              0.213445     0.698319      139.732773
0.387395
std               0.409912     0.870359       25.517636
0.487360
min               0.000000     0.000000       60.000000
0.000000
25%               0.000000     0.000000      121.000000
0.000000
50%               0.000000     0.000000      140.500000
0.000000
75%               0.000000     2.000000      160.000000
1.000000
max               1.000000     2.000000      202.000000
1.000000

           oldpeak     ST slope       target
count  1190.000000  1190.000000  1190.000000
mean      0.922773     1.624370     0.528571
std       1.086337     0.610459     0.499393
min      -2.600000     0.000000     0.000000
25%       0.000000     1.000000     0.000000
50%       0.600000     2.000000     1.000000
75%       1.600000     2.000000     1.000000
max       6.200000     3.000000     1.000000

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1190 entries, 0 to 1189
Data columns (total 12 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   age                  1190 non-null   int64
 1   sex                  1190 non-null   int64
 2   chest pain type      1190 non-null   int64
 3   resting bp s         1190 non-null   int64
 4   cholesterol          1190 non-null   int64
 5   fasting blood sugar  1190 non-null   int64
```

```
 6   resting ecg           1190 non-null   int64
 7   max heart rate        1190 non-null   int64
 8   exercise angina       1190 non-null   int64
 9   oldpeak               1190 non-null   float64
 10  ST slope              1190 non-null   int64
 11  target                1190 non-null   int64
dtypes: float64(1), int64(11)
memory usage: 111.7 KB
```

No need for null value removal as well as normalization as we already know no null vales present and no huge values in dataset so normalization isnt exactly necessary. We will proceed with checking for outliers and removing them if any.

```
from scipy import stats

numerical_cols_iqr = ['resting bp s', 'cholesterol', 'max heart rate',
'oldpeak']

for col in numerical_cols_iqr:
    if col in df.columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]
        print(f"IQR method applied to '{col}'. Current shape:
{df.shape}")
    else:
        print(f"Warning: Column '{col}' not found in the DataFrame for
IQR method.")
```

```
IQR method applied to 'resting bp s'. Current shape: (1153, 12)
IQR method applied to 'cholesterol'. Current shape: (968, 12)
IQR method applied to 'max heart rate'. Current shape: (968, 12)
IQR method applied to 'oldpeak'. Current shape: (952, 12)
```

Now we will proceed with the training and train it with a few algorithms to get the best one

```
#Importing Modules

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
```

```
from sklearn.metrics import accuracy_score, classification_report
import xgboost as xgb

#Necessary Steps

X = df.drop('target', axis=1)
y = df['target']

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42, stratify=y)
print(f"\nTraining set shape: {X_train.shape}, Test set shape:
{X_test.shape}")


Training set shape: (761, 11), Test set shape: (191, 11)

numerical_cols = X_train.select_dtypes(include=np.number).columns

scaler = StandardScaler()

X_train[numerical_cols] =
scaler.fit_transform(X_train[numerical_cols])

X_test[numerical_cols] = scaler.transform(X_test[numerical_cols])

#Logistic Regression

print("\n--- Logistic Regression ---")
log_reg_model = LogisticRegression(random_state=42,
solver='liblinear')
log_reg_model.fit(X_train, y_train)
y_pred_log_reg = log_reg_model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred_log_reg))
print("Classification Report:\n", classification_report(y_test,
y_pred_log_reg))


--- Logistic Regression ---
Accuracy: 0.7801047120418848
Classification Report:
              precision    recall  f1-score   support

           0       0.79      0.82      0.80       104
           1       0.77      0.74      0.75        87

    accuracy                           0.78       191
   macro avg       0.78      0.78      0.78       191
weighted avg       0.78      0.78      0.78       191


#Decision Tree
```

```
print("\n--- Decision Tree Classifier ---")
dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)
y_pred_dt = dt_model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred_dt))
print("Classification Report:\n", classification_report(y_test,
y_pred_dt))
```

```
--- Decision Tree Classifier ---
Accuracy: 0.9057591623036649
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.91      0.91       104
           1       0.90      0.90      0.90        87

    accuracy                           0.91       191
   macro avg       0.91      0.91      0.91       191
weighted avg       0.91      0.91      0.91       191
```

```
#Random Forest

print("\n--- Random Forest Classifier ---")
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred_rf))
print("Classification Report:\n", classification_report(y_test,
y_pred_rf))
```

```
--- Random Forest Classifier ---
Accuracy: 0.9109947643979057
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.89      0.92       104
           1       0.88      0.93      0.91        87

    accuracy                           0.91       191
   macro avg       0.91      0.91      0.91       191
weighted avg       0.91      0.91      0.91       191
```

```
#SVM

print("\n--- Support Vector Machine (SVM) ---")
svm_model = SVC(random_state=42)
svm_model.fit(X_train, y_train)
```

```
y_pred_svm = svm_model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred_svm))
print("Classification Report:\n", classification_report(y_test,
y_pred_svm))
```

```
--- Support Vector Machine (SVM) ---
Accuracy: 0.806282722513089
Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.77      0.81       104
           1       0.76      0.85      0.80        87

    accuracy                           0.81       191
   macro avg       0.81      0.81      0.81       191
weighted avg       0.81      0.81      0.81       191
```

```
#KNN

print("\n--- K-Nearest Neighbors (KNN) ---")
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train, y_train)
y_pred_knn = knn_model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred_knn))
print("Classification Report:\n", classification_report(y_test,
y_pred_knn))
```

```
--- K-Nearest Neighbors (KNN) ---
Accuracy: 0.8010471204188482
Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.80      0.81       104
           1       0.77      0.80      0.79        87

    accuracy                           0.80       191
   macro avg       0.80      0.80      0.80       191
weighted avg       0.80      0.80      0.80       191
```

```
#Gradient Boosting

print("\n--- Gradient Boosting Classifier (Bonus) ---")
gb_model = GradientBoostingClassifier(n_estimators=100,
learning_rate=0.1, random_state=42)
gb_model.fit(X_train, y_train)
y_pred_gb = gb_model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred_gb))
```

```
print("Classification Report:\n", classification_report(y_test,
y_pred_gb))
```

```
--- Gradient Boosting Classifier (Bonus) ---
Accuracy: 0.8900523560209425
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.88      0.90       104
           1       0.87      0.90      0.88        87

    accuracy                           0.89       191
   macro avg       0.89      0.89      0.89       191
weighted avg       0.89      0.89      0.89       191
```

```
#XGBoost

print("\n--- XGBoost Classifier ---")
xgb_model = xgb.XGBClassifier(objective='binary:logistic',
                              eval_metric='logloss',
                              use_label_encoder=False,
                              n_estimators=100,
                              learning_rate=0.1,
                              random_state=42
                             )
xgb_model.fit(X_train, y_train)
y_pred_xgb = xgb_model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred_xgb))
print("Classification Report:\n", classification_report(y_test,
y_pred_xgb))
```

```
--- XGBoost Classifier ---

C:\Users\tanis\AppData\Local\Packages\
PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-
packages\Python311\site-packages\xgboost\training.py:183: UserWarning:
[00:10:15] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\
learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)

Accuracy: 0.93717277486911
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.93      0.94       104
           1       0.92      0.94      0.93        87
```

```
    accuracy                           0.94       191
   macro avg       0.94      0.94      0.94       191
weighted avg       0.94      0.94      0.94       191
```

Hence , we can see XGBoost is the best algorithm for the following dataset. Lets try it with hyperparamater tuning and see if it can become better.

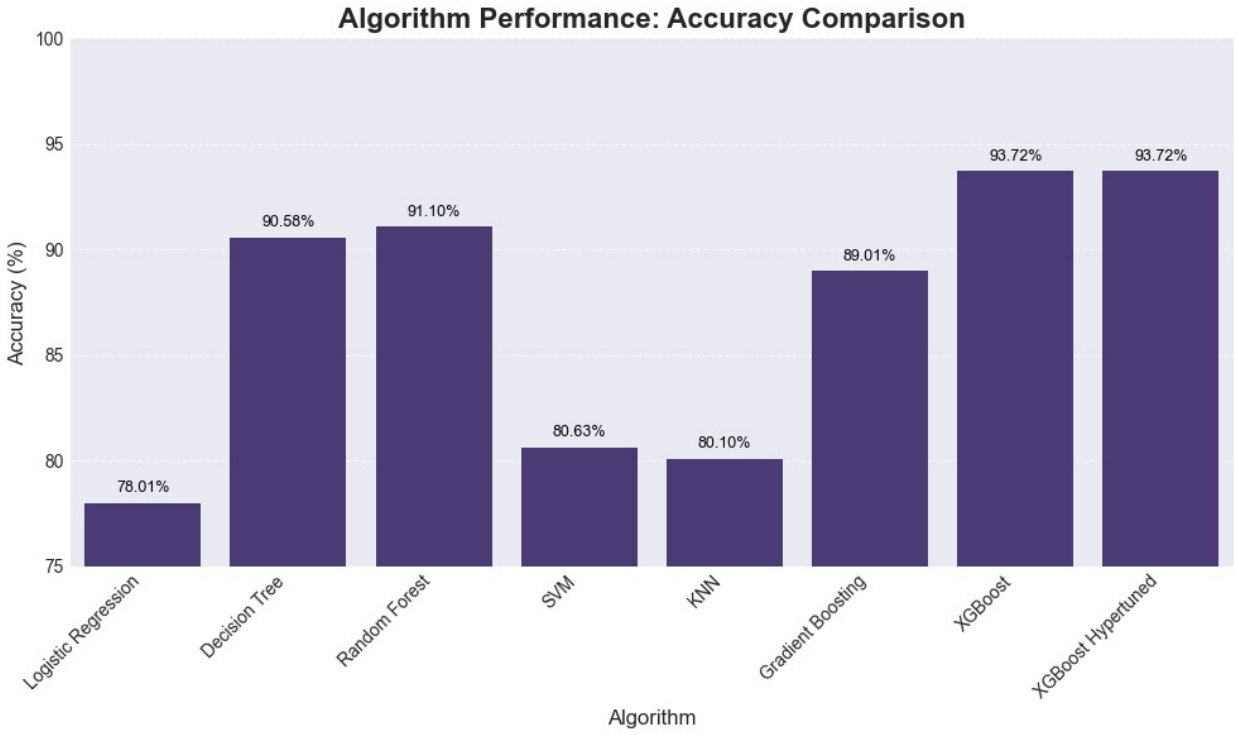
```
# XGBoost Hypertuned

from sklearn.model_selection import GridSearchCV

print("\n--- XGBoost Classifier with Hyperparameter Tuning
(GridSearchCV) ---")
xgb_model = xgb.XGBClassifier(objective='binary:logistic',
                              eval_metric='logloss',
                              use_label_encoder=False,
                              random_state=42
                             )
param_grid = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7],
    'subsample': [0.7, 0.8, 1.0],
    'colsample_bytree': [0.7, 0.8, 1.0],
    'gamma': [0, 0.1, 0.2]
}
grid_search = GridSearchCV(estimator=xgb_model,
                           param_grid=param_grid,
                           cv=5,
                           scoring='accuracy',
                           n_jobs=-1,
                           verbose=2)
print("\nStarting Grid Search for best hyperparameters... This might
take a while.")
grid_search.fit(X_train, y_train)
print("\nBest parameters found: ", grid_search.best_params_)
print("Best cross-validation accuracy:
{:.4f}".format(grid_search.best_score_))
best_xgb_model = grid_search.best_estimator_
print("\nTraining final XGBoost model with best parameters on the
entire training set...")
best_xgb_model.fit(X_train, y_train)
y_pred_best_xgb = best_xgb_model.predict(X_test)
print("\n--- Evaluation on Test Set with Best XGBoost Model ---")
print("Accuracy:", accuracy_score(y_test, y_pred_best_xgb))
print("Classification Report:\n", classification_report(y_test,
y_pred_best_xgb))
```

```
--- XGBoost Classifier with Hyperparameter Tuning (GridSearchCV) ---

Starting Grid Search for best hyperparameters... This might take a
while.
Fitting 5 folds for each of 729 candidates, totalling 3645 fits

C:\Users\tanis\AppData\Local\Packages\
PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-
packages\Python311\site-packages\xgboost\training.py:183: UserWarning:
[00:15:38] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\
learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
C:\Users\tanis\AppData\Local\Packages\
PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-
packages\Python311\site-packages\xgboost\training.py:183: UserWarning:
[00:15:38] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\
learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)


Best parameters found:  {'colsample_bytree': 0.8, 'gamma': 0.1,
'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 200,
'subsample': 1.0}
Best cross-validation accuracy: 0.9172

Training final XGBoost model with best parameters on the entire
training set...

--- Evaluation on Test Set with Best XGBoost Model ---
Accuracy: 0.93717277486911
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.94      0.94       104
           1       0.93      0.93      0.93        87

    accuracy                           0.94       191
   macro avg       0.94      0.94      0.94       191
weighted avg       0.94      0.94      0.94       191
```

Now , lets make a barchart to show all accuracies in a systematic manner.

```
import matplotlib.pyplot as plt
import seaborn as sns
```

```
#Graph

data = {
    'Algorithm': ['Logistic Regression', 'Decision Tree', 'Random
Forest', 'SVM', 'KNN', 'Gradient Boosting', 'XGBoost', 'XGBoost
Hypertuned'],
    'Accuracy': [78.01, 90.58, 91.1, 80.63, 80.1, 89.01, 93.72,
93.72],
}

df1 = pd.DataFrame(data)

plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette('viridis')

plt.figure(figsize=(10, 6))

sns.barplot(x='Algorithm', y='Accuracy', data=df1)

plt.title('Algorithm Performance: Accuracy Comparison', fontsize=16,
weight='bold')
plt.xlabel('Algorithm', fontsize=12)
plt.ylabel('Accuracy (%)', fontsize=12)
plt.ylim(75, 100)
plt.xticks(rotation=45, ha='right')

for index, row in df1.iterrows():
    plt.text(index, row['Accuracy'] + 0.5, f'{row["Accuracy"]:.2f}%',
             color='black', ha="center", fontsize=9)

plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()

plt.show()
```


Algorithm Performance: Accuracy Comparison
Accuracy (%)
100
95
90
85
80
75
78.01%
90.58%
91.10%
80.63%
80.10%
89.01%
93.72%
93.72%
Logistic Regression
Decision Tree
Random Forest
SVM
KNN
Gradient Boosting
XGBoost
XGBoost Hypertuned
Algorithm