Predictive Analytics for Patient Outcomes in Healthcare

This a prototype model of the predict analystics model, where we have used a sample dataset from kaggle, in order to understand the overall structure of the model which includes visualisation as well as model building

```
In [1]: import pandas as pd

# Load the dataset
file_path = 'C:/Users/varshithbr/Desktop/case study final exam/finaldatasetnew2.csv
df = pd.read_csv(file_path)

# Display the first few rows of the dataset
df.head()
```

U	и	L	L	+	J	0

JacksOn 1 LesLie TErRy A+ 37 1 2 130 250 0 1 18 2 DaNnY SMitH A- 41 0 1 130 204 0 0 17 3 andrEw waTtS O+ 56 1 1 120 236 0 1 17	.]:		Name	Blood Type	age	Sex	ChestPain	BloodPressure	Cholesterol	BloodSugar	ECG	HeartRat
1 TErRy A+ 37 1 2 130 250 0 1 18 2 DaNnY sMitH A- 41 0 1 130 204 0 0 17 3 andrEw waTtS O+ 56 1 1 120 236 0 1 17 4 adrIENNE AB+ 57 0 0 120 354 0 1 16		0	,	B-	63	1	3	145	233	1	0	150
2 sMith A- 41 0 1 130 204 0 0 17 3 andrEw waTtS O+ 56 1 1 120 236 0 1 17 4 adrIENNE AB+ 57 0 0 120 354 0 1 16		1		A+	37	1	2	130	250	0	1	18
3 waTtS O+ 56 1 1 120 236 0 1 17		2		A-	41	0	1	130	204	0	0	177
Δ ΔR+ 57 () () 120 35 Δ () 1 16		3		O+	56	1	1	120	236	0	1	178
		4		AB+	57	0	0	120	354	0	1	16.

Data cleaning

This is the process where we refine the data take it further for the EDA

```
In [130... # 1. Check for missing values
print("Missing Values:\n", df.isnull().sum())

# 2. Handle missing values by filling them with the mean (for numerical columns)
# df.fillna(df.mean(), inplace=True)

# 3. Check data types
print("\nData Types:\n", df.dtypes)
```

```
Missing Values:
               0
Name
Blood Type
age
Sex
ChestPain
BloodPressure
Cholesterol
BloodSugar
ECG
HeartRate
Angina
Depression
Slope
Vessels
Thalassemia
             0
output
dtype: int64
Data Types:
                object
Name
Blood Type
              object
age
                int64
Sex
                int64
ChestPain
               int64
BloodPressure
               int64
Cholesterol
               int64
               int64
BloodSugar
ECG
                int64
HeartRate
            int64
Angina
               int64
Depression float64
Slope
               int64
Vessels
               int64
Thalassemia
               int64
output
                int64
dtype: object
```

Exploratory data analysis

Here we get an idea of relationships, patterns and trends between the variables, so we are proceeding with the best insightful variables

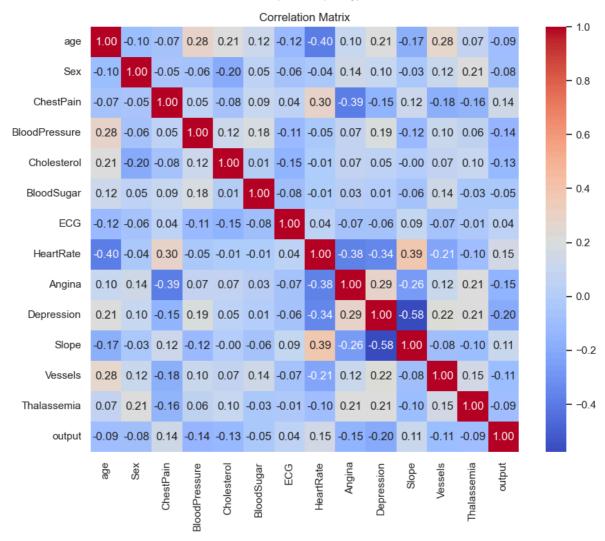
```
plt.title("Correlation Matrix")
plt.show()

# Distribution plots for numerical features
df.hist(bins=20, figsize=(15, 10))
plt.suptitle("Distribution of Numerical Features")
plt.show()

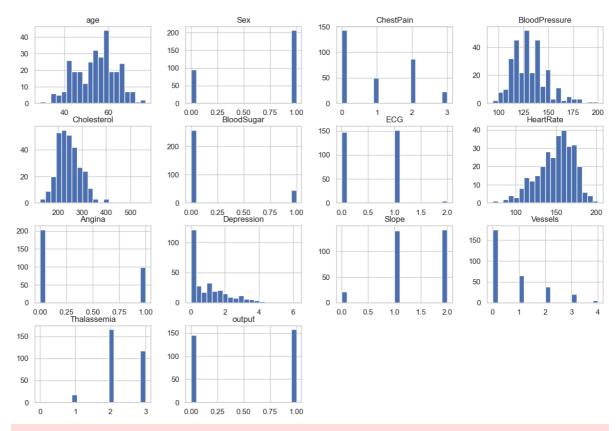
# Pairplot to visualize relationships between features
sns.pairplot(df, diag_kind='kde')
plt.suptitle("Pairplot of Features", y=1.02)
plt.show()

# Countplot for categorical variables (if any)
# Example: sns.countplot(x='categorical_column', data=df)
```

	age	Sex	ChestPain	BloodPressu	re Choleste	erol \	
count	303.000000	303.000000	303.000000	303.0000	00 303.000	000	
mean	54.366337	0.683168	0.966997	131.6237	62 246.264	026	
std	9.082101	0.466011	1.032052	17.5381	43 51.830	751	
min	29.000000	0.000000	0.000000	94.0000	00 126.000	1000	
25%	47.500000	0.000000	0.000000	120.0000	00 211.000	1000	
50%	55.000000	1.000000	1.000000	130.0000	00 240.000	000	
75%	61.000000	1.000000	2.000000	140.0000	00 274.500	000	
max	77.000000	1.000000	3.000000	200.0000	00 564.000	000	
	BloodSugar	ECG	HeartRate	Angina	Depression	Slope	\
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	
mean	0.148515	0.528053	149.646865	0.326733	1.039604	1.399340	
std	0.356198	0.525860	22.905161	0.469794	1.161075	0.616226	
min	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	133.500000	0.000000	0.000000	1.000000	
50%	0.000000	1.000000	153.000000	0.000000	0.800000	1.000000	
75%	0.000000	1.000000	166.000000	1.000000	1.600000	2.000000	
max	1.000000	2.000000	202.000000	1.000000	6.200000	2.000000	
	Vessels	Thalassemia	output				
count	303.000000	303.000000	303.000000				
mean	0.729373	2.313531	0.521452				
std	1.022606	0.612277	0.500366				
min	0.000000	0.000000	0.000000				
25%	0.000000	2.000000	0.000000				
50%	0.000000	2.000000	1.000000				
75%	1.000000	3.000000	1.000000				
max	4.000000	3.000000	1.000000				

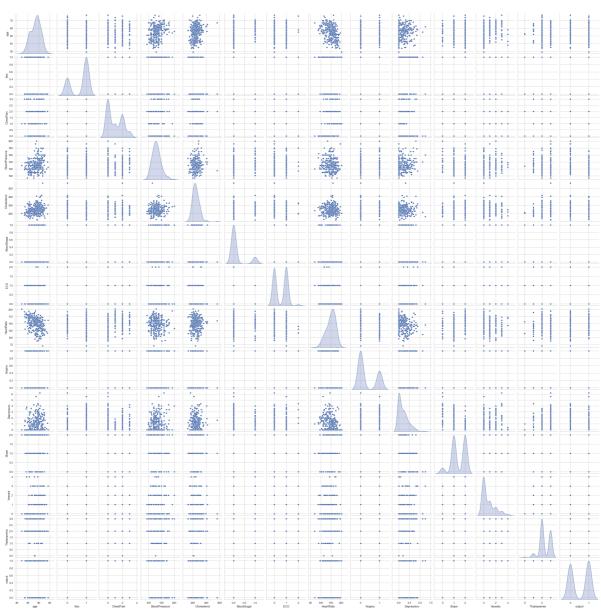


Distribution of Numerical Features



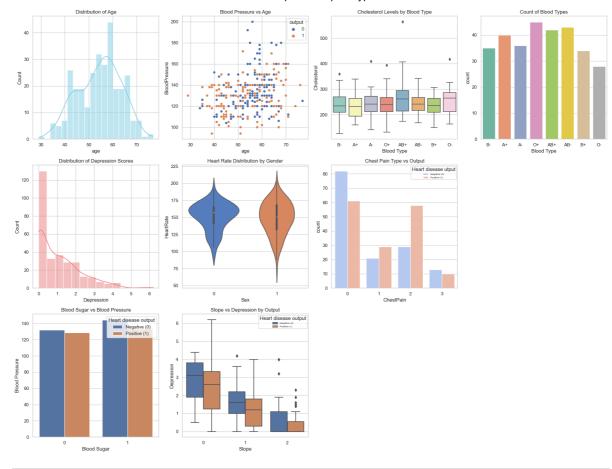
C:\Users\varshithbr\AppData\Local\Programs\Python\Python311\Lib\site-packages\seab
orn\axisgrid.py:118: UserWarning: The figure layout has changed to tight
 self._figure.tight_layout(*args, **kwargs)

Pairplot of Fea



```
import pandas as pd
In [183...
           import seaborn as sns
           import matplotlib.pyplot as plt
           import numpy as np
           # Load the CSV file
           rem = ['Name']
           # Drop the specified columns
           df_clean2 = df.drop(columns=rem)
           df = df_clean2
           # Set up the plotting environment
           sns.set(style="whitegrid")
           plt.figure(figsize=(20, 15))
           # 1. Distribution of Age
           plt.subplot(3, 4, 1)
           sns.histplot(df['age'], kde=True, bins=20, color='skyblue')
           plt.title('Distribution of Age')
           # 2. Blood Pressure vs Age
           plt.subplot(3, 4, 2)
           sns.scatterplot(x='age', y='BloodPressure', hue='output', data=df)
           plt.title('Blood Pressure vs Age')
```

```
# 3. Cholesterol Levels by Blood Type
plt.subplot(3, 4, 3)
sns.boxplot(x='Blood Type', y='Cholesterol', data=df, palette="Set3")
plt.title('Cholesterol Levels by Blood Type')
# 4. Count of Blood Types
plt.subplot(3, 4, 4)
sns.countplot(x='Blood Type', data=df, palette="Set2")
plt.title('Count of Blood Types')
# 5. Distribution of Depression Scores
plt.subplot(3, 4, 5)
sns.histplot(df['Depression'], kde=True, color='lightcoral')
plt.title('Distribution of Depression Scores')
# 6. Heart Rate Distribution by Gender (Sex)
plt.subplot(3, 4, 6)
sns.violinplot(x='Sex', y='HeartRate', data=df, palette="muted")
plt.title('Heart Rate Distribution by Gender')
# 7. Chest Pain Type vs Output
plt.subplot(3, 4, 7)
sns.countplot(x='ChestPain', hue='output', data=df, palette="coolwarm")
plt.title('Chest Pain Type vs Output')
count_plot = sns.countplot(x='ChestPain', hue='output', data=df, palette="coolwarm'
handles, labels = count_plot.get_legend_handles_labels()
labels = ['Negative (0)', 'Positive (1)']
count_plot.legend(handles, labels, title='Heart disease utput', prop={'size': 6}, ]
# 9. Blood Sugar vs Blood Pressure
plt.subplot(3, 4, 9)
sns.barplot(x='BloodSugar', y='BloodPressure', hue='output', data=df, ci=None)
plt.legend(title='Heart disease output', labels=['Negative (0)', 'Positive (1)'])
plt.title('Blood Sugar vs Blood Pressure')
plt.xlabel('Blood Sugar')
plt.ylabel('Blood Pressure')
# 10. Slope vs Depression by Output
plt.subplot(3, 4, 10)
sns.boxplot(x='Slope', y='Depression', hue='output', data=df)
plt.title('Slope vs Depression by Output')
count plot = sns.boxplot(x='Slope', y='Depression', hue='output', data=df)
handles, labels = count plot.get legend handles labels()
labels = ['Negative (0)', 'Positive (1)']
count_plot.legend(handles, labels, title='Heart disease output', prop={'size': 6},
# Adjust Layout
plt.tight layout()
plt.show()
C:\Users\varshithbr\AppData\Local\Temp\ipykernel 23636\3036792497.py:60: FutureWar
ning:
The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.
 sns.barplot(x='BloodSugar', y='BloodPressure', hue='output', data=df, ci=None)
```



```
import pandas as pd
In [95]:
         import seaborn as sns
         import matplotlib.pyplot as plt
         df = df_clean
         # Set up the plotting environment
         sns.set(style="whitegrid")
         plt.figure(figsize=(15, 10))
         # 1. Count of Patients with and without Heart Disease
         plt.subplot(3, 3, 1)
         sns.countplot(x='output', data=df, palette="Set1")
         plt.title('Count of Patients with and without Heart Disease')
         # 2. Age Distribution by Heart Disease Outcome
         plt.subplot(3, 3, 2)
         sns.histplot(df[df['output'] == 1]['age'], kde=True, color='red', label='Heart Dise
         sns.histplot(df[df['output'] == 0]['age'], kde=True, color='blue', label='No Heart
         plt.legend()
         plt.title('Age Distribution by Heart Disease Outcome')
         # 3. Blood Pressure by Heart Disease Outcome
         plt.subplot(3, 3, 3)
         sns.boxplot(x='output', y='BloodPressure', data=df, palette="Set2")
         plt.title('Blood Pressure by Heart Disease Outcome')
         # 4. Cholesterol Levels by Heart Disease Outcome
         plt.subplot(3, 3, 4)
         sns.boxplot(x='output', y='Cholesterol', data=df, palette="Set3")
         plt.title('Cholesterol Levels by Heart Disease Outcome')
         # 5. Heart Rate by Heart Disease Outcome
         plt.subplot(3, 3, 5)
         sns.boxplot(x='output', y='HeartRate', data=df, palette="Set1")
         plt.title('Heart Rate by Heart Disease Outcome')
```

```
# 6. Depression Levels by Heart Disease Outcome
plt.subplot(3, 3, 6)
sns.boxplot(x='output', y='Depression', data=df, palette="Set2")
plt.title('Depression Levels by Heart Disease Outcome')
# 7. Chest Pain Type by Heart Disease Outcome
plt.subplot(3, 3, 7)
sns.countplot(x='ChestPain', hue='output', data=df, palette="coolwarm")
plt.title('Chest Pain Type by Heart Disease Outcome')
# 8. Blood Sugar by Heart Disease Outcome
plt.subplot(3, 3, 8)
sns.countplot(x='BloodSugar', hue='output', data=df, palette="Set1")
plt.title('Blood Sugar by Heart Disease Outcome')
# 9. Correlation of Features with Heart Disease Outcome
plt.subplot(3, 3, 9)
correlation = df.corr()['output'].sort_values(ascending=False)
sns.barplot(x=correlation.index, y=correlation.values, palette="coolwarm")
plt.xticks(rotation=90)
plt.title('Correlation of Features with Heart Disease Outcome')
# Adjust Layout
plt.tight_layout()
plt.show()
                                                                                 Blood Pressure by Heart Disease Outcome
      Count of Patients with and without Heart Disea
                                                                          200
 150
                                             Heart Disease
                                                                          180
 125
  100
                                                                          160
                                     20
  75
                                                                          140
  50
                                                                         Bloo
                                                                          120
  25
                                                                          100
                  output
                                                                                           output
                                                       age
       Cholesterol Levels by Heart Disease Outcome
                                             Heart Rate by Heart Disease Outcome
                                                                                Depression Levels by Heart Disease Outcome
                                      200
 500
                                      175
Cholesterol
300
                                                                          Depression
                                    HeartRate
                                      150
                                      125
                                      100
 200
                  output
                                                      output
       Chest Pain Type by Heart Disease Outcome
                                             Blood Sugar by Heart Disease Outcome
                                                                              Correlation of Features with Heart Disease Outcome
                                                                          1.0
  80
                                                                   output
                              output
                                      125
                                                                          0.8
                                      100
  60
                                                                          0.6
40
                                      75
                                                                          0.4
                                      50
                                                                          0.2
                                      25
                                                                          -0.2
                                                0
                                                     BloodSuga
```

Model buidling

We have choose classification model and here we are going to be building several classification models in order to choose the best model for our project.

```
In [52]: from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import StandardScaler
    from sklearn.linear_model import LogisticRegression
```

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
df=df clean
# Define the target and features
X = df[['Depression', 'HeartRate', 'Angina', 'Slope']] # Replace 'target_column' with
y = df['output']
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
# Standardize the features (if necessary)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
# Build the logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)
# Predict on the test set
y_pred = model.predict(X_test)
# Evaluate the model
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("Accuracy:", accuracy_score(y_test, y_pred))
Confusion Matrix:
```

[[25 16] [15 35]]

Classification Report:

	precision	recall	f1-score	support
0	0.62	0.61	0.62	41
1	0.69	0.70	0.69	50
accuracy			0.66	91
macro avg	0.66	0.65	0.66	91
weighted avg	0.66	0.66	0.66	91

Accuracy: 0.6593406593406593

```
In [53]: from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler
         df = df_clean
         # Define the target and features
         X = df[['Depression', 'HeartRate', 'Angina', 'Slope']]
         y = df['output']
         # Split the data into training and testing sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
         # Standardize the features (if necessary)
         scaler = StandardScaler()
         X_train = scaler.fit_transform(X_train)
         X test = scaler.transform(X test)
         # Build the Random Forest model
         model = RandomForestClassifier(n estimators=100, random state=42)
         model.fit(X_train, y_train)
```

```
# Predict on the test set
y_pred = model.predict(X_test)
# Evaluate the model
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("Accuracy:", accuracy_score(y_test, y_pred))
Confusion Matrix:
 [[26 15]
 [25 25]]
Classification Report:
                            recall f1-score
               precision
                                                support
           0
                   0.51
                             0.63
                                        0.57
                                                    41
                              0.50
           1
                                        0.56
                                                    50
                   0.62
                                        0.56
                                                    91
    accuracy
                              0.57
   macro avg
                   0.57
                                        0.56
                                                    91
                             0.56
                                        0.56
                                                    91
weighted avg
                   0.57
```

Accuracy: 0.5604395604395604

```
In [54]: from sklearn.ensemble import GradientBoostingClassifier
         from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
         from sklearn.model selection import train test split
         from sklearn.preprocessing import StandardScaler
         df = df clean
         # Define the target and features
         X = df[['Depression','HeartRate','Angina','Slope']]
         y = df['output']
         # Split the data into training and testing sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
         # Standardize the features (if necessary)
         scaler = StandardScaler()
         X_train = scaler.fit_transform(X_train)
         X_test = scaler.transform(X_test)
         # Build the Gradient Boosting model
         model = GradientBoostingClassifier(n estimators=100, random state=42)
         model.fit(X_train, y_train)
         # Predict on the test set
         y_pred = model.predict(X_test)
         # Evaluate the model
         print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
         print("\nClassification Report:\n", classification report(y test, y pred))
         print("Accuracy:", accuracy_score(y_test, y_pred))
```

Confusion Matrix:

[[26 15] [22 28]]

```
Classification Report:
                         precision
                                   recall f1-score
                                                         support
                     0
                             0.54
                                       0.63
                                                 0.58
                                                             41
                     1
                                       0.56
                                                 0.60
                                                             50
                             0.65
             accuracy
                                                 0.59
                                                             91
            macro avg
                             0.60
                                       0.60
                                                 0.59
                                                             91
                                       0.59
                                                 0.59
                                                             91
         weighted avg
                             0.60
         Accuracy: 0.5934065934065934
In [55]: | from sklearn.svm import SVC
          from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
          from sklearn.model_selection import train_test_split
          from sklearn.preprocessing import StandardScaler
          df = df_clean
          # Define the target and features
         X = df[['Depression', 'HeartRate', 'Angina', 'Slope']]
          y = df['output']
          # Split the data into training and testing sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
          # Standardize the features (if necessary)
          scaler = StandardScaler()
          X train = scaler.fit transform(X train)
          X_test = scaler.transform(X_test)
          # Build the SVM model with RBF kernel
          model = SVC(kernel='rbf', C=1, gamma='scale', random_state=42)
          model.fit(X_train, y_train)
          # Predict on the test set
          y pred = model.predict(X test)
          # Evaluate the model
          print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
          print("\nClassification Report:\n", classification_report(y_test, y_pred))
          print("Accuracy:", accuracy_score(y_test, y_pred))
         Confusion Matrix:
          [[25 16]
          [19 31]]
         Classification Report:
                         precision
                                     recall f1-score
                                                         support
                             0.57
                                       0.61
                                                 0.59
                                                             41
                                                             50
                                       0.62
                     1
                             0.66
                                                 0.64
                                                 0.62
                                                             91
             accuracy
                             0.61
                                       0.61
                                                 0.61
                                                             91
            macro avg
         weighted avg
                             0.62
                                       0.62
                                                 0.62
                                                             91
         Accuracy: 0.6153846153846154
In [56]: models = {
              'Logistic Regression': LogisticRegression(),
```

```
'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42),
    'Gradient Boosting': GradientBoostingClassifier(n_estimators=100, random_state=
    'SVM (RBF Kernel)': SVC(kernel='rbf', C=1, gamma='scale', random_state=42)
accuracies = {}
# Train and evaluate each model
for name, model in models.items():
    model.fit(X_train, y_train)
   y_pred = model.predict(X_test)
    accuracies[name] = accuracy_score(y_test, y_pred)
# Plotting the accuracies
plt.figure(figsize=(10, 6))
plt.bar(accuracies.keys(), accuracies.values(), color=['blue', 'green', 'red', 'pur
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.title('Model Accuracy Comparison')
plt.ylim([0, 1])
plt.show()
```

