*** *Diabetes Prediction* ***

Step1: Importing the libraries.

In [311…

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn import svm
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
```

Step 2: Loading a Data

In [313…

```
diabetes_dataset  = pd.read_excel('diabetes_data.xlnx')
```

In [314…

```
print(diabetes_dataset)
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6      148             72             35        0  33.6
1              1       85             66             29        0  26.6
2              8      183             64              0        0  23.3
3              1       89             66             23       94  28.1
4              0      137             40             35      168  43.1
..           ...      ...            ...            ...      ...   ...
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age  Outcome
0                       0.627   50        1
1                       0.351   31        0
2                       0.672   32        1
3                       0.167   21        0
4                       2.288   33        1
..                        ...  ...      ...
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
766                     0.349   47        1
767                     0.315   23        0

[768 rows x 9 columns]
```

In [315…

```
diabetes_dataset.head()
```

Out[315…

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeF
0	6	148	72	35	0	33.6	
1	1	85	66	29	0	26.6	
2	8	183	64	0	0	23.3	
3	1	89	66	23	94	28.1	
4	0	137	40	35	168	43.1	

Step3: Performing a mapping or transformation on a specific column

In [317…

```
diabetes_dataset.shape
```

Out[317…

```
(768, 9)
```

In [ ]:

In [318…

```
diabetes_dataset['Outcome'].value_counts()
```

Out[318…

```
Outcome
0    500
1    268
Name: count, dtype: int64
```

Step 3: Creating a new binary column named “Outcome.”by using mapping

In [320…

```
# Step 3: Map Outcome Column to Binary Values
diabetes_dataset['Outcome'] = diabetes_dataset['Outcome'].map({1: 'Diabetic', 0:
print("Updated Outcome column:")
print(diabetes_dataset.head())
```

```
Updated Outcome column:
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age       Outcome
0                     0.627   50      Diabetic
1                     0.351   31  Non-diabetic
2                     0.672   32      Diabetic
3                     0.167   21  Non-diabetic
4                     2.288   33      Diabetic
```

In [321…

```
# separating the data and lables
X = diabetes_dataset.drop(columns= 'Outcome',axis = 1)
Y = diabetes_dataset['Outcome']
```

In [322…

```
diabetes_dataset.head()
```

Out[322…

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeF
0	6	148	72	35	0	33.6	
1	1	85	66	29	0	26.6	
2	8	183	64	0	0	23.3	
3	1	89	66	23	94	28.1	
4	0	137	40	35	168	43.1	

Step 4: Creating a histogram using 'plt.hist' to visualize the distribution of the "Outcome" column

In [324…

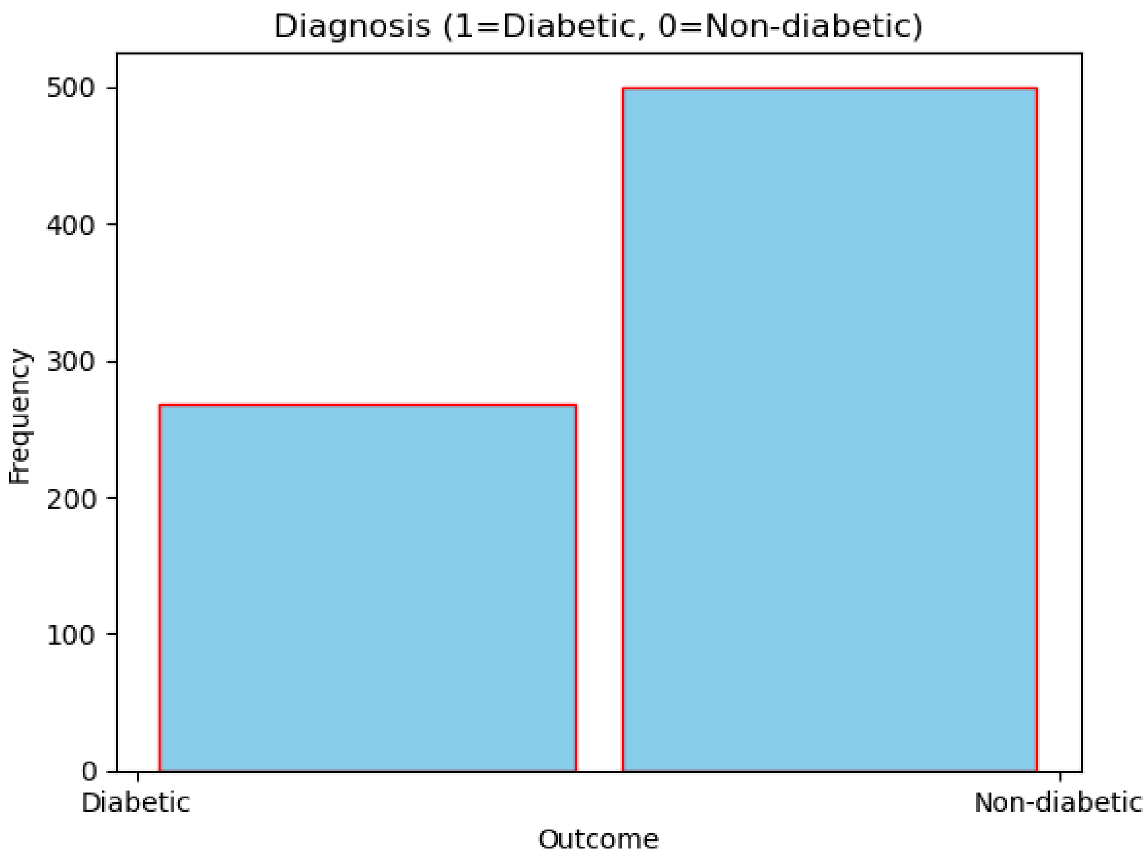
```
diabetes_dataset.describe()
```

Out[324…

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000

In [325…

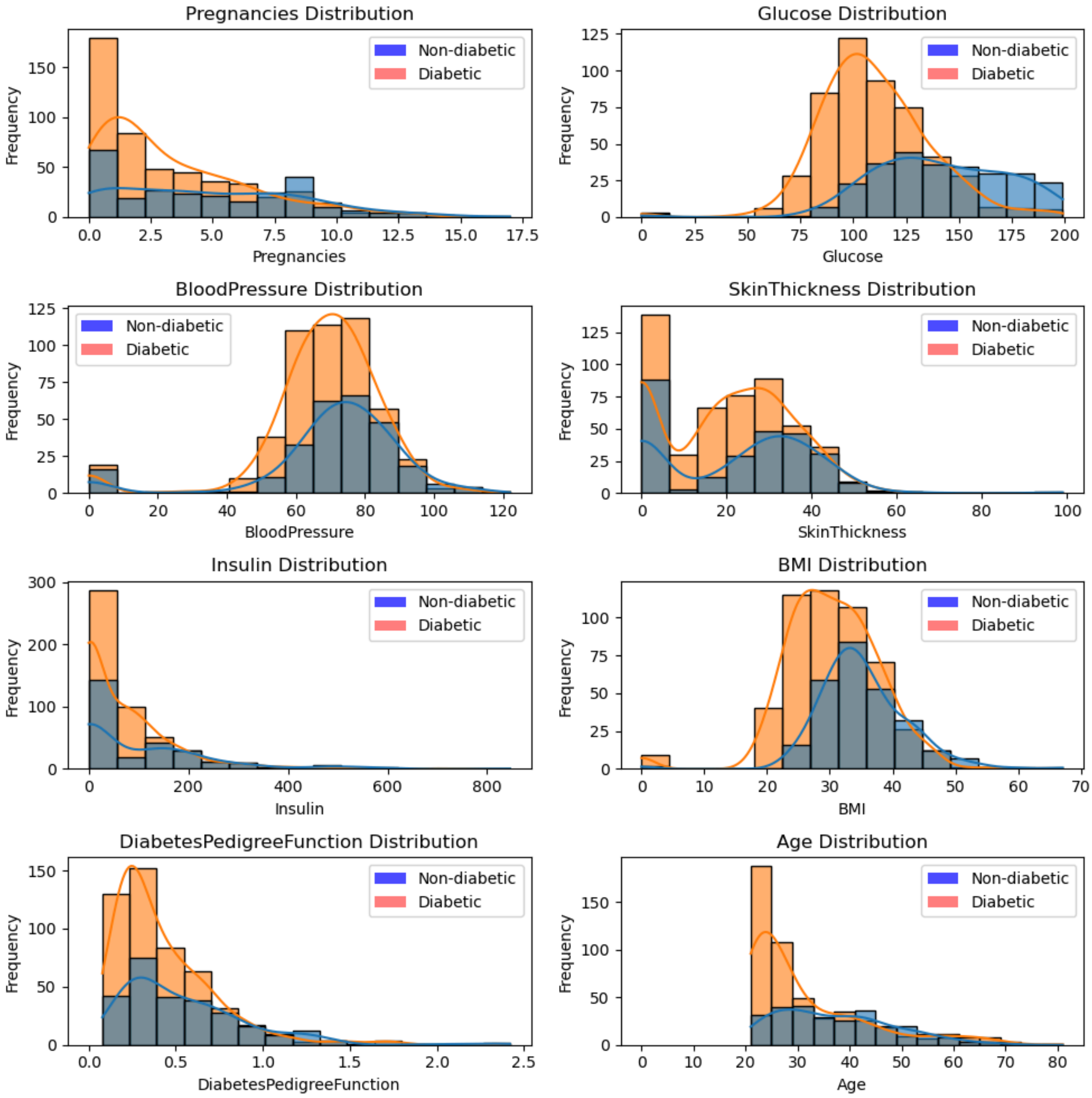
```
# Create histogram for 'Outcome' column
plt.hist(diabetes_dataset['Outcome'], bins=2, edgecolor='r', color='skyblue', rw
plt.title('Diagnosis (1=Diabetic, 0=Non-diabetic)')
plt.xlabel('Outcome')
plt.ylabel('Frequency')
plt.show()
```



Step 5: Creating a set of histograms for various features

In [327…

```
# Define features to visualize
X = ['Pregnancies','Glucose','BloodPressure','SkinThickness','Insulin','BMI','Di

# Create subplots
plt.figure(figsize=(10, 10))

for i, X in enumerate(X):
    plt.subplot(4, 2, i + 1)  # Create a subplot grid of 3x2

    # Plot histogram for non-diabetic cases
    plt.hist(diabetes_dataset[diabetes_dataset['Outcome'] == 0][X], bins=15, col

    # Plot histogram for diabetic cases
    plt.hist(diabetes_dataset[diabetes_dataset['Outcome'] == 1][X], bins=15, col
    sns.histplot(data=diabetes_dataset, x=X, hue='Outcome', kde=True, bins=15, a
    # Add title and legend
    plt.title(f'{X} Distribution')
    plt.xlabel(X)
    plt.ylabel('Frequency')
    plt.legend()

# Adjust layout
plt.tight_layout()

# Display the histograms
plt.show()
```



Step 6: Data Standardising

In [329...

```
# data standardising
scaler = StandardScaler()
```

In [395...

```
scaler.fit(X)
standardized_data = scaler.transform(X)
```

In [397...

```
print(standardized_data)
```

```
[[ 0.63994726  0.84832379  0.14964075 ...  0.20401277  0.46849198
   1.4259954 ]
 [-0.84488505 -1.12339636 -0.16054575 ... -0.68442195 -0.36506078
  -0.19067191]
 [ 1.23388019  1.94372388 -0.26394125 ... -1.10325546  0.60439732
  -0.10558415]
 ...
 [ 0.3429808   0.00330087  0.14964075 ... -0.73518964 -0.68519336
  -0.27575966]
 [-0.84488505  0.1597866  -0.47073225 ... -0.24020459 -0.37110101
   1.17073215]
 [-0.84488505 -0.8730192   0.04624525 ... -0.20212881 -0.47378505
  -0.87137393]]
```

In [399…
```
X = standardized_data
Y = diabetes_dataset['Outcome']
```

In [401…
```
print(X)
print(Y)
```

```
[[ 0.63994726  0.84832379  0.14964075 ...  0.20401277  0.46849198
   1.4259954 ]
 [-0.84488505 -1.12339636 -0.16054575 ... -0.68442195 -0.36506078
  -0.19067191]
 [ 1.23388019  1.94372388 -0.26394125 ... -1.10325546  0.60439732
  -0.10558415]
 ...
 [ 0.3429808   0.00330087  0.14964075 ... -0.73518964 -0.68519336
  -0.27575966]
 [-0.84488505  0.1597866  -0.47073225 ... -0.24020459 -0.37110101
   1.17073215]
 [-0.84488505 -0.8730192   0.04624525 ... -0.20212881 -0.47378505
  -0.87137393]]
0          Diabetic
1      Non-diabetic
2          Diabetic
3      Non-diabetic
4          Diabetic
           ...
763    Non-diabetic
764    Non-diabetic
765    Non-diabetic
766        Diabetic
767    Non-diabetic
Name: Outcome, Length: 768, dtype: object
```

In [403…
```
diabetes_dataset.groupby('Outcome').mean()
```

Out[403…

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI
Outcome						
Diabetic	4.865672	141.257463	70.824627	22.164179	100.335821	35.142537
Non-diabetic	3.298000	109.980000	68.184000	19.664000	68.792000	30.304200

Step 7: Splitting the data into training and

testing sets

In [406…
```
# train test split
X_train,X_test,Y_train,Y_test = train_test_split(X,Y, test_size=0.3, stratify=Y,
```

In [408…
```
# Split the dataset into training and testing sets
train_diabetes_dataset, test_diabetes_dataset = train_test_split(diabetes_datase

# Print the sizes of the training and testing sets
print(f'Training set size: {len(train_diabetes_dataset)} rows')
print(f'Testing set size: {len(test_diabetes_dataset)} rows')
```

```
Training set size: 537 rows
Testing set size: 231 rows
```

Step 8: Training the model by using Support Vector Machine

In [411…
```
#training the model
```

In [413…
```
model = svm.SVC(kernel = 'linear')
```

In [415…
```
# training the support vecctor machine clasifier
model.fit(X_train,Y_train)
```

Out[415…
```
SVC
SVC(kernel='linear')
```

In [417…
```
# model evaluation
```

In [419…
```
#accuracy score
```

In [421…
```
# accuracy score on the training data
X_train_prediction = model.predict(X_train)
training_data_accuracy = accuracy_score(X_train_prediction,Y_train)
```

In [423…
```
print(f'Training Accuracy: {training_data_accuracy:.2f}')
```

```
Training Accuracy: 0.78
```

In [425…
```
# accuracy score on the testing data
X_test_prediction = model.predict(X_test)
testing_data_accuracy = accuracy_score(X_test_prediction,Y_test )
```

In [427…
```
print(f'Testing Accuracy: {testing_data_accuracy:.2f}')
```

```
Testing Accuracy: 0.77
```

Step 9: Classification model

In [430…
```
def classification_model(model, X_train, X_test, Y_train, Y_test, n_folds=5):
    # Train the model
    model.fit(X_train, Y_train)

    # Predict and evaluate
    predictions = model.predict(X_test)
    accuracy = accuracy_score(Y_test, predictions)
    print(f'Testing Accuracy: {accuracy:.2f}')

    # Cross-validation
    cv_scores = cross_val_score(model, X_train, Y_train, cv=n_folds)
    print(f'Mean Cross-Validation Score: {cv_scores.mean():.2f}')
classification_model(model, X_train, X_test, Y_train, Y_test, n_folds=5)
```

```
Testing Accuracy: 0.77
Mean Cross-Validation Score: 0.78
```

Step 10: Logistic Regression model

In [460…
```python
#  Logistic Regression model
logistic_model = LogisticRegression()
classification_model(logistic_model, X_train, X_test, Y_train, Y_test)
# Create a Logistic Regression model
model = LogisticRegression()  # Increase max_iter for potential convergence issu

# Train the model
model.fit(X_train, Y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(Y_test, y_pred)
print(f"Accuracy: {accuracy}")

# Print the confusion matrix
conf_matrix = confusion_matrix(Y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

```
Testing Accuracy: 0.78
Mean Cross-Validation Score: 0.77
Accuracy: 0.7792207792207793
Confusion Matrix:
[[ 48  33]
 [ 18 132]]
```

In [462…
```python
#makin a predictive system
```

In [464…
```python
input_data = (4,110,92,0,0,37.6,0.191,30)
```

In [466…
```python
#changing the input data to numpy array
input_data_as_numpy_array = np.asarray(input_data)
# reshape the array as we are predicting for one instance
input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)
# standardized the input data
std_data = scaler.transform(input_data_reshaped)
print(std_data)
prediction = model.predict(std_data)
print(prediction)
if (prediction[0]== 0):
    print('The person is not diabetic')
else:
    print('THe person is daibetic')
```

```
[[ 4.00000000e+00  1.10000000e+02  9.20000000e+01 -5.20417043e-17
   1.61907524e-17  3.76000000e+01  1.91000000e-01  3.00000000e+01]]
['Diabetic']
THe person is daibetic
```

In [474…
```python
input_data = (1,85,66,29,0,26.6,0.351,31)
```

In [476…
```python
#changing the input data to numpy array
input_data_as_numpy_array = np.asarray(input_data)
# reshape the array as we are predicting for one instance
input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)
# standardized the input data
std_data = scaler.transform(input_data_reshaped)
```

```
print(std_data)
prediction = model.predict(std_data)
print(prediction)
if (prediction[0]== 0):
    print('The person is not diabetic')
else:
    print('THe person is daibetic')
```

```
[[1.00000000e+00 8.50000000e+01 6.60000000e+01 2.90000000e+01
  1.61907524e-17 2.66000000e+01 3.51000000e-01 3.10000000e+01]]
['Diabetic']
THe person is daibetic
```

Step 11: Conclusion

By systematically following the steps outlined in the diabetes prediction workflow, you can create a robust process for evaluating multiple machine learning models. After data preprocessing, visualization, and standardization, you used models like Support Vector Machines (SVM) and Logistic Regression to classify individuals as diabetic or non-diabetic. Key Highlights: Data Understanding and Preprocessing: Analyzed the dataset structure, performed necessary transformations, and handled scaling to prepare the data for modeling. Visualized feature distributions and relationships using histograms and other plots to gain insights into the data. Model Evaluation: SVM achieved an accuracy of 77% on the test dataset, demonstrating its potential for linear classification tasks. Logistic Regression offered a slightly better test accuracy of 78%, along with a comparable cross-validation score of 77%, showcasing its efficiency for binary classification. Comparison of Metrics: Metrics such as accuracy, confusion matrix, and cross-validation scores were used to determine each model's predictive performance and reliability. Logistic Regression demonstrated slightly better generalization capabilities compared to SVM, as seen in the confusion matrix where false negatives were relatively fewer. Model Selection: Based on the chosen metrics and the task's requirements, Logistic Regression could be considered the more effective model for this dataset. Real-World Application: Predictive systems were developed using both models to classify new input data. Example cases demonstrated how the models could predict whether a person is diabetic based on their health metrics. Next Steps: Evaluate additional machine learning models, such as Decision Trees, Random Forest, or Gradient Boosting, to explore their effectiveness on the same dataset. Experiment with hyperparameter tuning to optimize the models further. If needed, explore ensemble techniques to combine the strengths of multiple models for better accuracy and robustness. By comparing and contrasting the performance of different algorithms, the most suitable model can be deployed for the given classification problem, ensuring reliable predictions in real-world scenarios.