Diabetes Risk Prediction using Machine Learning

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Problem Statement

- Diabetes is a very common disease with may risk factors that can lead to getting diabetes.
- We have to predict whether an individual is at risk of having early stage diabetes given the signs and symptoms.
- Since we are using an already labelled dataset to build a predictive model, our task will be a supervised machine learning problem.
- Therefore we will be using a supervised machine learning classification approach to solve our problem.

Dataset Information

- Datasource
    - https://archive.ics.uci.edu/dataset/529/early+stage+diabetes+risk+prediction+data:
- Description

  - The dataset contains the signs and symptpoms data of newly diabetic or would be diabetic patient.
  - The dataset was published in Computer Vision and Machine Intelligence in Medical Image Analysis.
- Metadata
  - The dataset is multivariate in nature and in a CSV format.
  - It has 520 datapoints and 17 fields or attributes.
- Attribute Information
  - Age 20-65
  - Gender 1. Male, 2.Female
  - Polyuria 1.Yes, 2.No.
  - Polydipsia 1.Yes, 2.No.
  - Sudden Weight Loss 1.Yes, 2.No.
  - Weakness 1.Yes, 2.No.
  - Polyphagia 1.Yes, 2.No.
  - Genital Thrush 1.Yes, 2.No.
  - Visual Blurring 1.Yes, 2.No.
  - Itching 1.Yes, 2.No.
  - Irritability 1.Yes, 2.No.
  - Delayed Healing 1.Yes, 2.No.
  - Partial Paresis 1.Yes, 2.No.
  - Muscle Stiffness 1.Yes, 2.No.
  - Alopecia 1.Yes, 2.No.
  - Obesity 1.Yes, 2.No.
  - Class 1.Positive, 2.Negative.

Data Preprocessing

In [1]:
```
# Load EDA(Exploratory Data Analysis) Packages
import numpy as np
import pandas as pd
```

In [2]:
```
# Load Data Vizualization Packages
from matplotlib import pyplot as plt
import seaborn as sns
```

In [3]:
```
# Load Machine Learning Packages
import sklearn
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
```

In [4]:
```
# Import model evaluation metrics
from sklearn.metrics import accuracy_score, classification_report, confusion_mat
from sklearn.model_selection import train_test_split
```

In [5]:
```python
# Check Package Versions
print("Pandas version: ", pd.__version__)
print("Numpy version: ", np.__version__)
print("Seaborn version: ", sns.__version__)
print("Sklearn version: ", sklearn.__version__)
```

```
Pandas version:  2.2.3
Numpy version:  2.1.3
Seaborn version:  0.13.2
Sklearn version:  1.6.1
```

In [6]:
```python
import warnings
warnings.filterwarnings("ignore")
```

Descriptive Analysis of Dataset

In [7]:
```python
# Load the dataset
df = pd.read_csv("data/diabetes_data_upload.csv")
```

In [8]:
```python
# Preview the first five rows
df.head()
```

Out[8]:

	Age	Gender	Polyuria	Polydipsia	sudden weight loss	weakness	Polyphagia	Genital thrush	visual blurring
0	40	Male	No	Yes	No	Yes	No	No	No
1	58	Male	No	No	No	Yes	No	No	Yes
2	41	Male	Yes	No	No	Yes	Yes	No	No
3	45	Male	No	No	Yes	Yes	Yes	Yes	No
4	60	Male	Yes	Yes	Yes	Yes	Yes	No	Yes

In [9]:
```python
# Check the dimension of the dataset
df.shape
```

Out[9]:
```
(520, 17)
```

In [10]:
```python
# Check for column names
df.columns
```

Out[10]:
```
Index(['Age', 'Gender', 'Polyuria', 'Polydipsia', 'sudden weight loss',
       'weakness', 'Polyphagia', 'Genital thrush', 'visual blurring',
       'Itching', 'Irritability', 'delayed healing', 'partial paresis',
       'muscle stiffness', 'Alopecia', 'Obesity', 'class'],
      dtype='object')
```

In [11]:
```python
# Check column data types
df.dtypes
```

Out[11]:
```
Age                     int64
Gender                 object
Polyuria               object
Polydipsia             object
sudden weight loss     object
weakness               object
Polyphagia             object
Genital thrush         object
visual blurring        object
Itching                object
Irritability           object
delayed healing        object
partial paresis        object
muscle stiffness       object
Alopecia               object
Obesity                object
class                  object
dtype: object
```

In [12]:
```
# Check how many missing values we have
df.isnull().sum()
```

Out[12]:
```
Age                    0
Gender                 0
Polyuria               0
Polydipsia             0
sudden weight loss     0
weakness               0
Polyphagia             0
Genital thrush         0
visual blurring        0
Itching                0
Irritability           0
delayed healing        0
partial paresis        0
muscle stiffness       0
Alopecia               0
Obesity                0
class                  0
dtype: int64
```

Narrative

- There are no missing values and we have 520 datapoints and 17 columns
- Most of the columns/fields are of the Object type. We will need to convert them to a proper format

Data Cleaning and Transformation

- Convert the column names to a consistent case and format.
- Encode the dataset into numeric format using either LabelEncoder or custom function
  - Gender: Female(0), Male(1)
  - Other Features: No(0), Yes(1)

In [13]:
```python
df.columns = df.columns.str.lower().str.replace(' ', '_')
```

In [14]:
```python
df.columns
```

Out[14]:
```
Index(['age', 'gender', 'polyuria', 'polydipsia', 'sudden_weight_loss',
       'weakness', 'polyphagia', 'genital_thrush', 'visual_blurring',
       'itching', 'irritability', 'delayed_healing', 'partial_paresis',
       'muscle_stiffness', 'alopecia', 'obesity', 'class'],
      dtype='object')
```

In [15]:
```python
#Encode the dataset
from sklearn.preprocessing import LabelEncoder
```

In [16]:
```python
objList = df.select_dtypes(include='object').columns
```

In [17]:
```python
objList
```

Out[17]:
```
Index(['gender', 'polyuria', 'polydipsia', 'sudden_weight_loss', 'weakness',
       'polyphagia', 'genital_thrush', 'visual_blurring', 'itching',
       'irritability', 'delayed_healing', 'partial_paresis',
       'muscle_stiffness', 'alopecia', 'obesity', 'class'],
      dtype='object')
```

In [18]:
```python
columns_to_label_encode = ['polyuria', 'polydipsia', 'sudden_weight_loss', 'weak
       'polyphagia', 'genital_thrush', 'visual_blurring', 'itching',
       'irritability', 'delayed_healing', 'partial_paresis',
       'muscle_stiffness', 'alopecia', 'obesity']
```

In [19]:
```python
label_encoder = LabelEncoder()
```

In [20]:
```python
# Encode every column except age, gender and class
for col in columns_to_label_encode:
    df[col] = label_encoder.fit_transform(df[col].astype(str))
```

In [21]:
```python
df.dtypes
```

Out[21]:
```
age                    int64
gender                object
polyuria               int64
polydipsia             int64
sudden_weight_loss     int64
weakness               int64
polyphagia             int64
genital_thrush         int64
visual_blurring        int64
itching                int64
irritability           int64
delayed_healing        int64
partial_paresis        int64
muscle_stiffness       int64
alopecia               int64
obesity                int64
class                 object
dtype: object
```

In [22]:
```python
df.head()
```

Out[22]:

	age	gender	polyuria	polydipsia	sudden_weight_loss	weakness	polyphagia	genit
0	40	Male	0	1	0	1	0	
1	58	Male	0	0	0	1	0	
2	41	Male	1	0	0	1	1	
3	45	Male	0	0	1	1	1	
4	60	Male	1	1	1	1	1	

In [23]:
```
# List Initial Classes
print(label_encoder.classes_)
```

```
['No' 'Yes']
```

In [24]:
```
# Using custom function for encoding gender and class columns
gender_map = {"Female":0, "Male":1}
target_label_map = {"Negative":0, "Positive":1}
```

In [25]:
```
df['gender'].unique()
```

Out[25]:
```
array(['Male', 'Female'], dtype=object)
```

In [26]:
```
df['gender'] = df['gender'].map(gender_map)
```

In [27]:
```
df['gender'].head()
```

Out[27]:
```
0    1
1    1
2    1
3    1
4    1
Name: gender, dtype: int64
```

In [28]:
```
# For target label, get unique values
df['class'].unique()
```

Out[28]:
```
array(['Positive', 'Negative'], dtype=object)
```

In [29]:
```
# Encode the target class using a mapping dictionary
df['class'] = df['class'].map(target_label_map)
```

In [30]:
```
# Recheck Datatypes
df.dtypes
```

Out[30]:
```
age                  int64
gender               int64
polyuria             int64
polydipsia           int64
sudden_weight_loss   int64
weakness             int64
polyphagia           int64
genital_thrush       int64
visual_blurring      int64
itching              int64
irritability         int64
delayed_healing      int64
partial_paresis      int64
muscle_stiffness     int64
alopecia             int64
obesity              int64
class                int64
dtype: object
```

In [31]:
```
# Recheck using Info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 520 entries, 0 to 519
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   age                 520 non-null    int64
 1   gender              520 non-null    int64
 2   polyuria            520 non-null    int64
 3   polydipsia          520 non-null    int64
 4   sudden_weight_loss  520 non-null    int64
 5   weakness            520 non-null    int64
 6   polyphagia          520 non-null    int64
 7   genital_thrush      520 non-null    int64
 8   visual_blurring     520 non-null    int64
 9   itching             520 non-null    int64
 10  irritability        520 non-null    int64
 11  delayed_healing     520 non-null    int64
 12  partial_paresis     520 non-null    int64
 13  muscle_stiffness    520 non-null    int64
 14  alopecia            520 non-null    int64
 15  obesity             520 non-null    int64
 16  class               520 non-null    int64
dtypes: int64(17)
memory usage: 69.2 KB
```

In [32]:
```
# Descriptive summary
df.describe()
```

Out[32]:

	age	gender	polyuria	polydipsia	sudden_weight_loss	weakness
count	520.000000	520.000000	520.000000	520.000000	520.000000	520.000000
mean	48.028846	0.630769	0.496154	0.448077	0.417308	0.586538
std	12.151466	0.483061	0.500467	0.497776	0.493589	0.492928
min	16.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	39.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	47.500000	1.000000	0.000000	0.000000	0.000000	1.000000
75%	57.000000	1.000000	1.000000	1.000000	1.000000	1.000000
max	90.000000	1.000000	1.000000	1.000000	1.000000	1.000000

In [41]:

```
df.head()
```

Out[41]:

	age	gender	polyuria	polydipsia	sudden_weight_loss	weakness	polyphagia	genit
0	40	1	0	1	0	1	0	
1	58	1	0	0	0	1	0	
2	41	1	1	0	0	1	1	
3	45	1	0	0	1	1	1	
4	60	1	1	1	1	1	1	

Narrative

- From the descriptive summary, the minimum age is 16 and the maximum age is 90
- We will have to get the distribution of data as per the age

In [34]:

```
# Value count per class
df['class'].value_counts()
```

Out[34]:

```
class
1    320
0    200
Name: count, dtype: int64
```

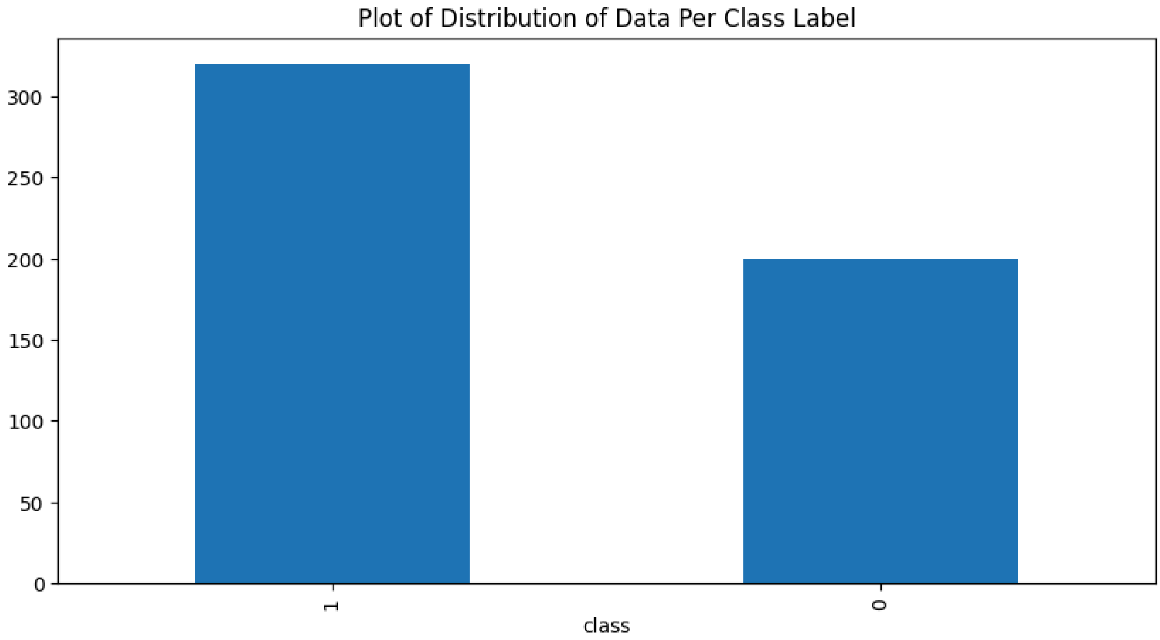
Narrative

- Our dataset has
  - 320 datapoints for class 1(Positive)
  - 200 datapoints for class 0(Negative)
- This looks like a balanced dataset from the plot of the value counts

In [35]:

```
# Plot of distribution of data per class label
plt.figure(figsize=(10,5))
plt.title("Plot of Distribution of Data Per Class Label")
```

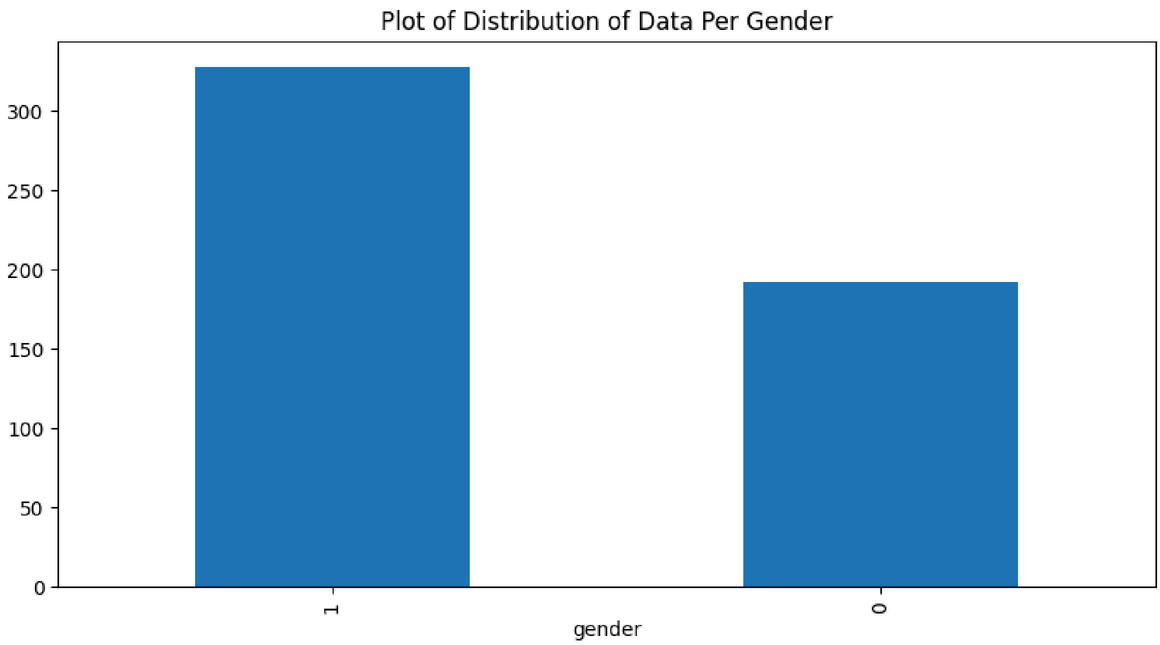
```python
df['class'].value_counts().plot(kind='bar')
plt.show()
```



In [36]:
```python
# Value count of Gender
df['gender'].value_counts()
```

Out[36]:
```
gender
1    328
0    192
Name: count, dtype: int64
```

In [37]:
```python
# Plot of Distribution of Data Per Gender
plt.figure(figsize=(10,5))
plt.title("Plot of Distribution of Data Per Gender")
df['gender'].value_counts().plot(kind='bar')
plt.show()
```



Narrative

- Our dataset has
  - 328 datapoints for class 1(Male)
  - 192 datapoints for class 0(Female)

In [38]:
```
### find the minimum and maximum age
print("Maximum age: ", df['age'].max())
print("Minimum age: ", df['age'].min())
```

```
Maximum age:  90
Minimum age:  16
```

In [39]:
```
labels = ["less than 10", "10-20", "20-30", "30-40", "40-50", "50-60", "60-70",
bins = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90]
```

In [40]:
```
freq_df = df.groupby(pd.cut(df['age'],bins=bins, labels=labels)).size()
```

In [41]:
```
freq_df.head()
```

Out[41]:
```
age
less than 10      0
10-20             1
20-30            44
30-40           123
40-50           145
dtype: int64
```

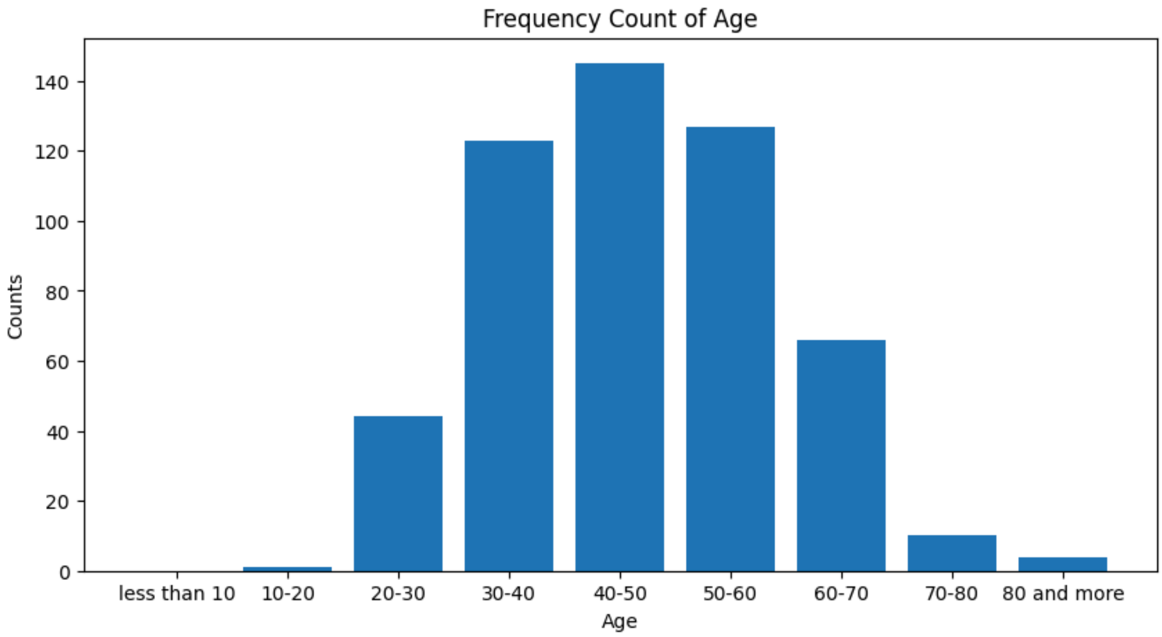
In [42]:
```
freq_df = freq_df.reset_index(name='count')
```

In [43]:
```
freq_df.head()
```

Out[43]:

	age	count
0	less than 10	0
1	10-20	1
2	20-30	44
3	30-40	123
4	40-50	145

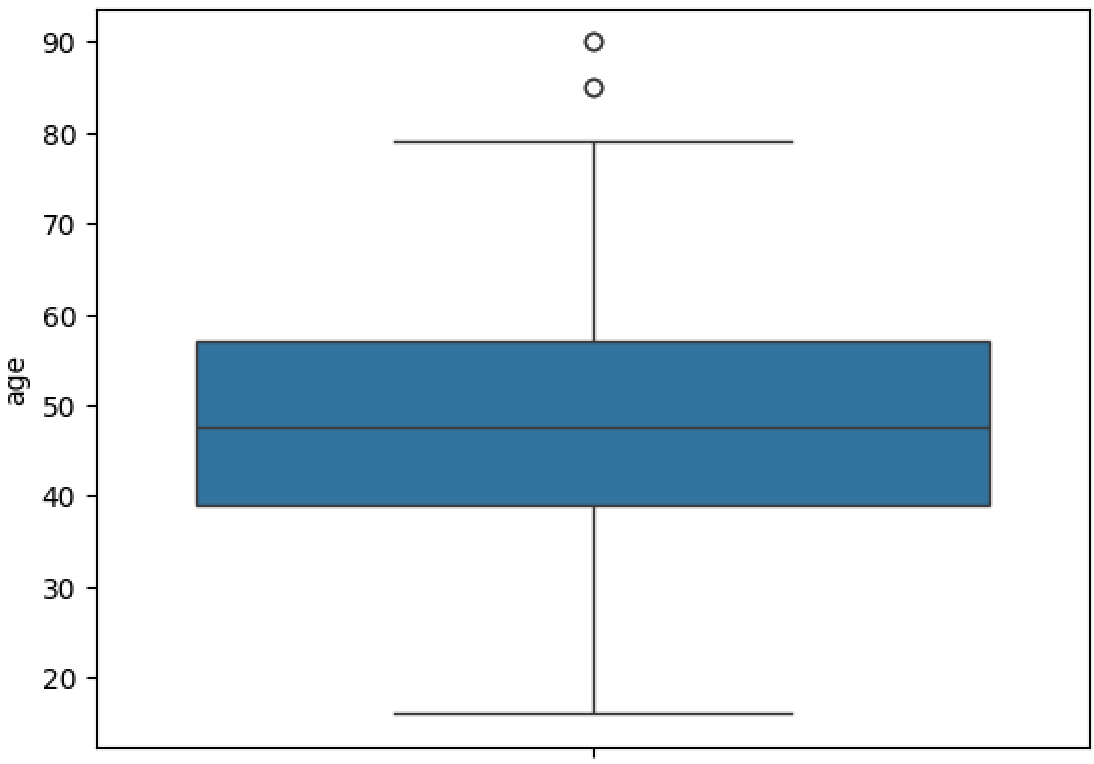
In [44]:
```
# Plot of distribution of data per gender (using Matplotlib)
plt.figure(figsize=(10,5))
plt.bar(freq_df['age'], freq_df['count'])
plt.xlabel('Age')
plt.ylabel('Counts')
plt.title('Frequency Count of Age')
plt.show()
```



In [45]:
```
freq_df.to_csv("data/frequency_distribution_age.csv")
```

In [46]:
```
# Find outliers in age using Boxplot
sns.boxplot(df['age'])
```

Out[46]: <Axes: ylabel='age'>



Correlation Analysis of Features in Relation to Target Class

- We will explore the dataset to see if there is an association between the features and the target class label

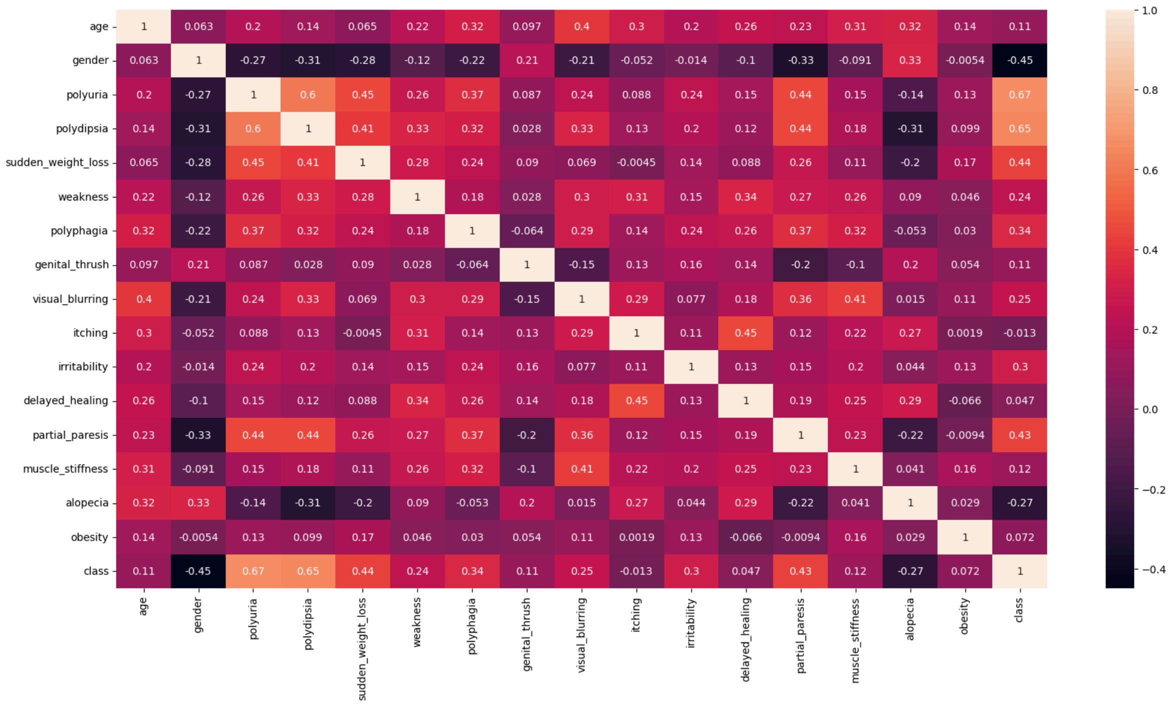
In [47]:
```
# Using dataframe's corr() method
df.corr()
```

Out[47]:

	age	gender	polyuria	polydipsia	sudden_weight_loss	wea
age	1.000000	0.062872	0.199781	0.137382	0.064808	0.2
gender	0.062872	1.000000	-0.268894	-0.312262	-0.281840	-0.1
polyuria	0.199781	-0.268894	1.000000	0.598609	0.447207	0.2
polydipsia	0.137382	-0.312262	0.598609	1.000000	0.405965	0.3
sudden_weight_loss	0.064808	-0.281840	0.447207	0.405965	1.000000	0.2
weakness	0.224596	-0.124490	0.263000	0.332453	0.282884	1.0
polyphagia	0.315577	-0.219968	0.373873	0.316839	0.243511	0.1
genital_thrush	0.096519	0.208961	0.087273	0.028081	0.089858	0.0
visual_blurring	0.402729	-0.208092	0.235095	0.331250	0.068754	0.3
itching	0.296559	-0.052496	0.088289	0.128716	-0.004516	0.3
irritability	0.201625	-0.013735	0.237740	0.203446	0.140340	0.1
delayed_healing	0.257501	-0.101978	0.149873	0.115691	0.088140	0.3
partial_paresis	0.232742	-0.332288	0.441664	0.442249	0.264014	0.2
muscle_stiffness	0.307703	-0.090542	0.152938	0.180723	0.109756	0.2
alopecia	0.321691	0.327871	-0.144192	-0.310964	-0.202727	0.0
obesity	0.140458	-0.005396	0.126567	0.098691	0.169294	0.0
class	0.108679	-0.449233	0.665922	0.648734	0.436568	0.2

In [48]:

```
# Plot correlation using Seaborn's Heatmap
plt.figure(figsize=(20,10))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



In [49]:
```
df.to_csv("data/diabetes_data_clean.csv", index=False)
```

Machine Learning Model Development, Prediction and Evaluation

- We will approach the supervised machine learning classification problem using several algorithms namely,
  - Logistic Regression
  - Decision Tree Classifier
  - Random Forest Classifier
  - Support Vector Classifier

Logistic Regression Model

In [50]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, roc_curve, auc
from sklearn.model_selection import cross_val_score, KFold
```

In [51]:
```
# Features and Labels
# Which columns are for features and for labels
X = df[['age', 'gender', 'polyuria', 'polydipsia', 'sudden_weight_loss', 'weakne
y=df['class']
```

In [52]:
```
# Features
print(X.columns)
```

```
Index(['age', 'gender', 'polyuria', 'polydipsia', 'sudden_weight_loss',
       'weakness', 'polyphagia', 'genital_thrush', 'visual_blurring',
       'itching', 'irritability', 'delayed_healing', 'partial_paresis',
       'muscle_stiffness', 'alopecia', 'obesity'],
      dtype='object')
```

In [53]:
```
# Split the dataset into training and testing set
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_
```

In [54]:
```
# Using LogisticRegression estimator to build a model
lr_model = LogisticRegression()
lr_model.fit(x_train, y_train)
```

Out[54]:
```
▾ LogisticRegression
LogisticRegression()
```

In [55]:
```
# Check model accuracy
# Method 1
print("Training set score: ", lr_model.score(x_train, y_train))
print("Test Set Score: ",lr_model.score(x_test, y_test))
```

```
Training set score:  0.9313186813186813
Test Set Score:  0.9358974358974359
```

In [56]:
```
# Hyperparameter tuning of Logistic Regression Model
from sklearn.model_selection import GridSearchCV
param_grid =  {
    'penalty' : ['l1', 'l2', 'elasticnet', 'none'],
    'C' : [0.001, 0.01, 0.1, 1, 10, 100],
    'solver' : ['lbfgs','newton-cg','liblinear','sag','saga'],
    'max_iter' : [100, 1000,2500, 5000]
}

lr_grid_search = GridSearchCV(LogisticRegression(), param_grid, verbose=True, cv
lr_grid_search.fit(x_train, y_train)
y_pred_lr_grid_search = lr_grid_search.predict(x_test)
print("Training set score: ", lr_grid_search.score(x_train, y_train))
print("Test Set Score: ",lr_grid_search.score(x_test, y_test))

print("Best parameters: ", lr_grid_search.best_params_)
print("Best cross validation score: {:.2f}".format(lr_grid_search.best_score_))
print("Best estimator: ", lr_grid_search.best_estimator_)
```

```
Fitting 5 folds for each of 480 candidates, totalling 2400 fits
Training set score:  0.9148351648351648
Test Set Score:  0.9294871794871795
Best parameters:  {'C': 0.1, 'max_iter': 100, 'penalty': 'l2', 'solver': 'libline
ar'}
Best cross validation score: 0.91
Best estimator:  LogisticRegression(C=0.1, solver='liblinear')
```

In [57]:
```
# Prediction of the Logistic Regression model on the test dataset (first 10 rows
lr_grid_search.predict(x_test[0:10])
```

Out[57]:
```
array([0, 1, 1, 1, 1, 1, 1, 0, 1, 0])
```

In [58]:
```
# Prediction probability of the above samples
lr_prob=lr_grid_search.predict_proba(x_test[0:10])
```

```
for i, prob in enumerate(lr_prob):
    print(f"Sample {i+1}: Class 0 Probability = {prob[0]:.3f}, Class 1 Probabili
```

```
Sample 1: Class 0 Probability = 0.540, Class 1 Probability = 0.460
Sample 2: Class 0 Probability = 0.057, Class 1 Probability = 0.943
Sample 3: Class 0 Probability = 0.088, Class 1 Probability = 0.912
Sample 4: Class 0 Probability = 0.039, Class 1 Probability = 0.961
Sample 5: Class 0 Probability = 0.422, Class 1 Probability = 0.578
Sample 6: Class 0 Probability = 0.026, Class 1 Probability = 0.974
Sample 7: Class 0 Probability = 0.384, Class 1 Probability = 0.616
Sample 8: Class 0 Probability = 0.623, Class 1 Probability = 0.377
Sample 9: Class 0 Probability = 0.484, Class 1 Probability = 0.516
Sample 10: Class 0 Probability = 0.838, Class 1 Probability = 0.162
```

In [59]:
```
from sklearn.metrics import classification_report, confusion_matrix
```

In [60]:
```
target_names = ['Negative(0)', 'Positive(1)']
```

In [61]:
```
# Classification Report (Logistic Regression Grid Search)
print(classification_report(y_test, y_pred_lr_grid_search, target_names=target_n
```

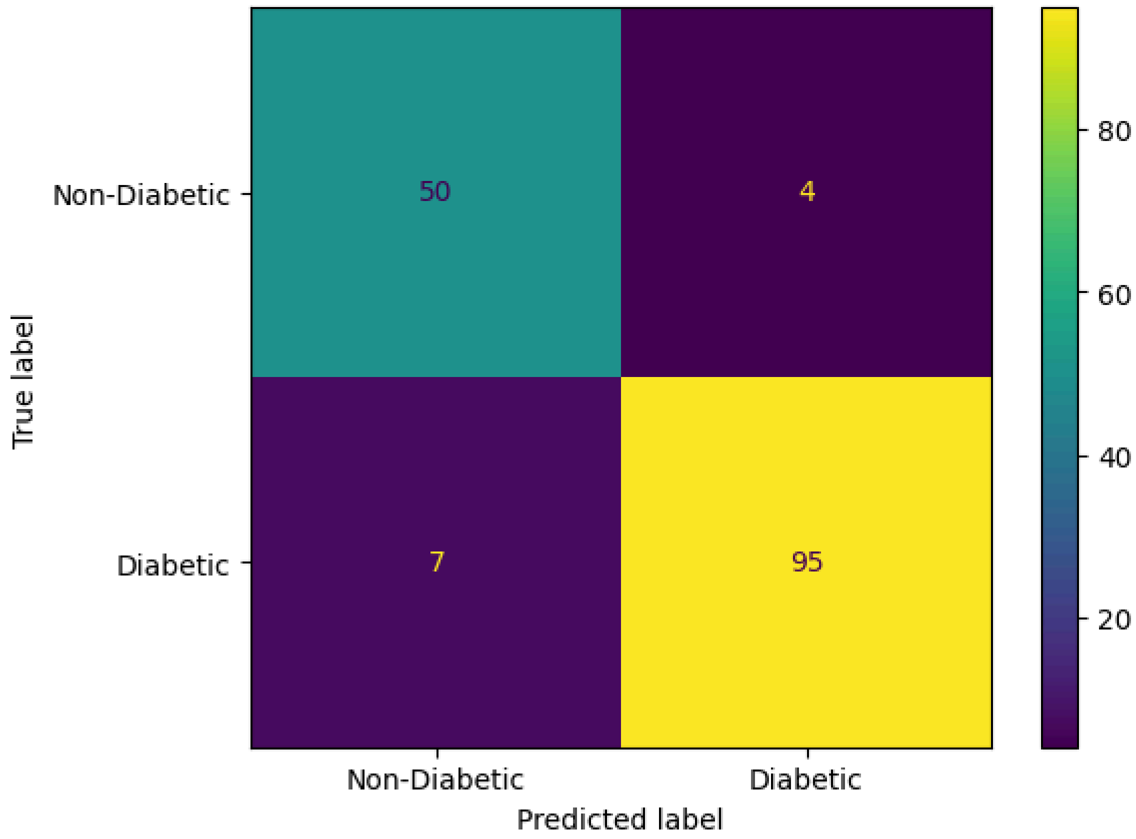
```
              precision    recall  f1-score   support

 Negative(0)       0.88      0.93      0.90        54
 Positive(1)       0.96      0.93      0.95       102

    accuracy                           0.93       156
   macro avg       0.92      0.93      0.92       156
weighted avg       0.93      0.93      0.93       156
```

In [62]:
```
# Save the classification report to csv file
clf_report=classification_report(y_test, y_pred_lr_grid_search, target_names=tar
report_df = pd.DataFrame(clf_report).transpose()
report_df.to_csv("model_evaluation/logistic_regression/lr_clf_report.csv")
```

In [63]:
```
# Confusion Matrix
conf_matrix=confusion_matrix(y_test, y_pred_lr_grid_search)
print(conf_matrix)
```

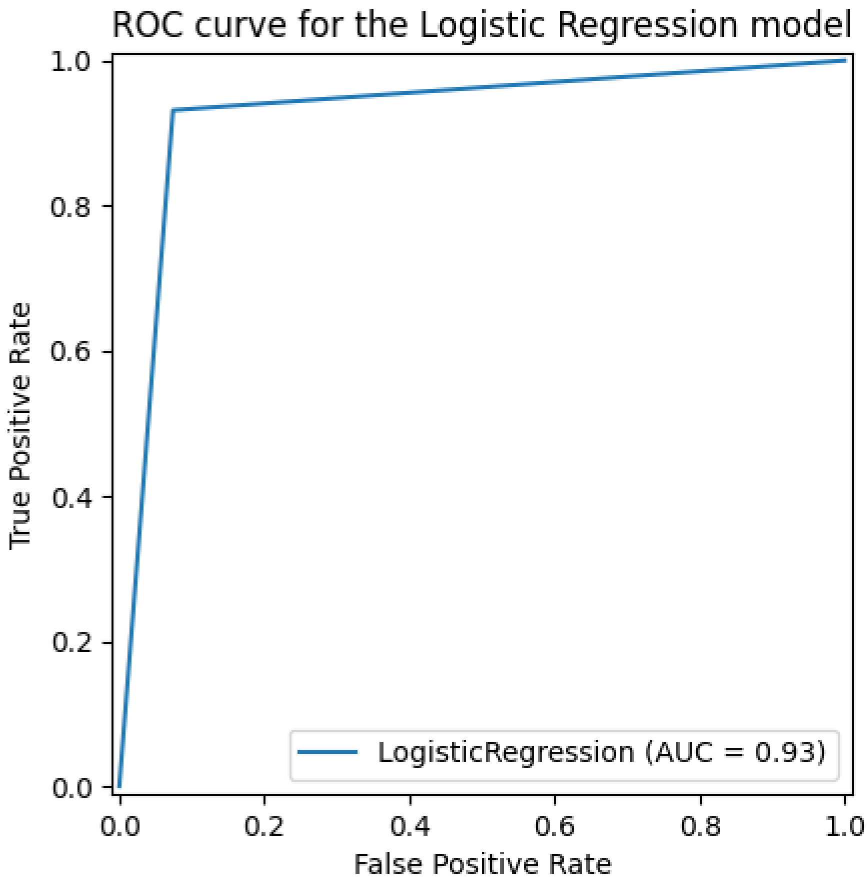
```
[[50  4]
 [ 7 95]]
```

In [64]:
```
# Plot Confusion Matrix
from sklearn.metrics import ConfusionMatrixDisplay, RocCurveDisplay
conf_matrix_display=ConfusionMatrixDisplay(conf_matrix, display_labels = ["Non-D
conf_matrix_display.plot()
plt.savefig('model_evaluation/logistic_regression/lr_confusion_matrix.png', dpi=
plt.show()
```



In [65]:

```
# Plot ROC Curve for Logistic Regression model
fpr, tpr, threshold = roc_curve(y_test, y_pred_lr_grid_search)
roc_auc = auc(fpr, tpr)
roc_display = RocCurveDisplay(fpr=fpr, tpr=tpr)
roc_display.plot(label='LogisticRegression (AUC = %.2f)' % roc_auc)
plt.savefig('model_evaluation/logistic_regression/lr_roc_curve.png', dpi=100, bb
plt.title("ROC curve for the Logistic Regression model")
plt.show()
```



In [66]:
```
# Cross Validation of the Logistic Regression
# Get the index of the best estimator
best_index = lr_grid_search.best_index_

# Extract scores for the best estimator
best_cv_scores = lr_grid_search.cv_results_["split0_test_score"][best_index], \
                 lr_grid_search.cv_results_["split1_test_score"][best_index], \
                 lr_grid_search.cv_results_["split2_test_score"][best_index], \
                 lr_grid_search.cv_results_["split3_test_score"][best_index], \
                 lr_grid_search.cv_results_["split4_test_score"][best_index]

best_cv_scores = [float(score) for score in best_cv_scores]
mean_test_score = lr_grid_search.cv_results_["mean_test_score"][best_index]
std_test_score = lr_grid_search.cv_results_["std_test_score"][best_index]

print("Best Index: ", best_index)
print("Best Estimator: ", lr_grid_search.best_estimator_)
print("Cross-validation scores of the best estimator:", best_cv_scores)
print("Mean accuracy:", mean_test_score)
print("Standard deviation:", std_test_score)
```

```
Best Index:  167
Best Estimator:  LogisticRegression(C=0.1, solver='liblinear')
Cross-validation scores of the best estimator: [0.9178082191780822, 0.86301369863
0137, 0.9315068493150684, 0.8767123287671232, 0.9444444444444444]
Mean accuracy: 0.9066971080669711
Standard deviation: 0.031531472227607105
```

Decision Tree Model

In [67]:
```python
# Create the Decision Tree Classifier model
dt_model = DecisionTreeClassifier()
```

In [68]:
```python
# Fit the model
dt_model.fit(x_train, y_train)
```

Out[68]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [69]:
```python
print("Training set score: ", dt_model.score(x_train, y_train))
print("Test set score: ", dt_model.score(x_test, y_test))
```

```
Training set score:  1.0
Test set score:  0.9551282051282052
```

In [70]:
```python
# Decision tree with depth 5
dt_model_depth5 = DecisionTreeClassifier(max_depth=5, random_state=0)
dt_model_depth5.fit(x_train, y_train)
print("Training set score: ", dt_model_depth5.score(x_train, y_train))
print("Test set score: ", dt_model_depth5.score(x_test, y_test))
```

```
Training set score:  0.9752747252747253
Test set score:  0.9551282051282052
```

In [71]:
```python
# Prediction of the Decision Tree model on the test dataset (first 10 rows)
dt_model_depth5.predict(x_test[0:10])
```

Out[71]:
```
array([0, 1, 1, 1, 1, 1, 1, 0, 1, 0])
```

In [72]:
```python
# Prediction probability of the above samples
dt_prob=dt_model_depth5.predict_proba(x_test[0:10])
for i, prob in enumerate(dt_prob):
    print(f"Sample {i+1}: Class 0 Probability = {prob[0]:.3f}, Class 1 Probabili
```

```
Sample 1: Class 0 Probability = 1.000, Class 1 Probability = 0.000
Sample 2: Class 0 Probability = 0.000, Class 1 Probability = 1.000
Sample 3: Class 0 Probability = 0.000, Class 1 Probability = 1.000
Sample 4: Class 0 Probability = 0.000, Class 1 Probability = 1.000
Sample 5: Class 0 Probability = 0.000, Class 1 Probability = 1.000
Sample 6: Class 0 Probability = 0.000, Class 1 Probability = 1.000
Sample 7: Class 0 Probability = 0.000, Class 1 Probability = 1.000
Sample 8: Class 0 Probability = 0.857, Class 1 Probability = 0.143
Sample 9: Class 0 Probability = 0.000, Class 1 Probability = 1.000
Sample 10: Class 0 Probability = 0.984, Class 1 Probability = 0.016
```

In [73]:
```python
# Classification report for our Decision Tree model
y_pred_dt_depth5 = dt_model_depth5.predict(x_test)
print(classification_report(y_test, y_pred_dt_depth5, target_names=target_names))
```

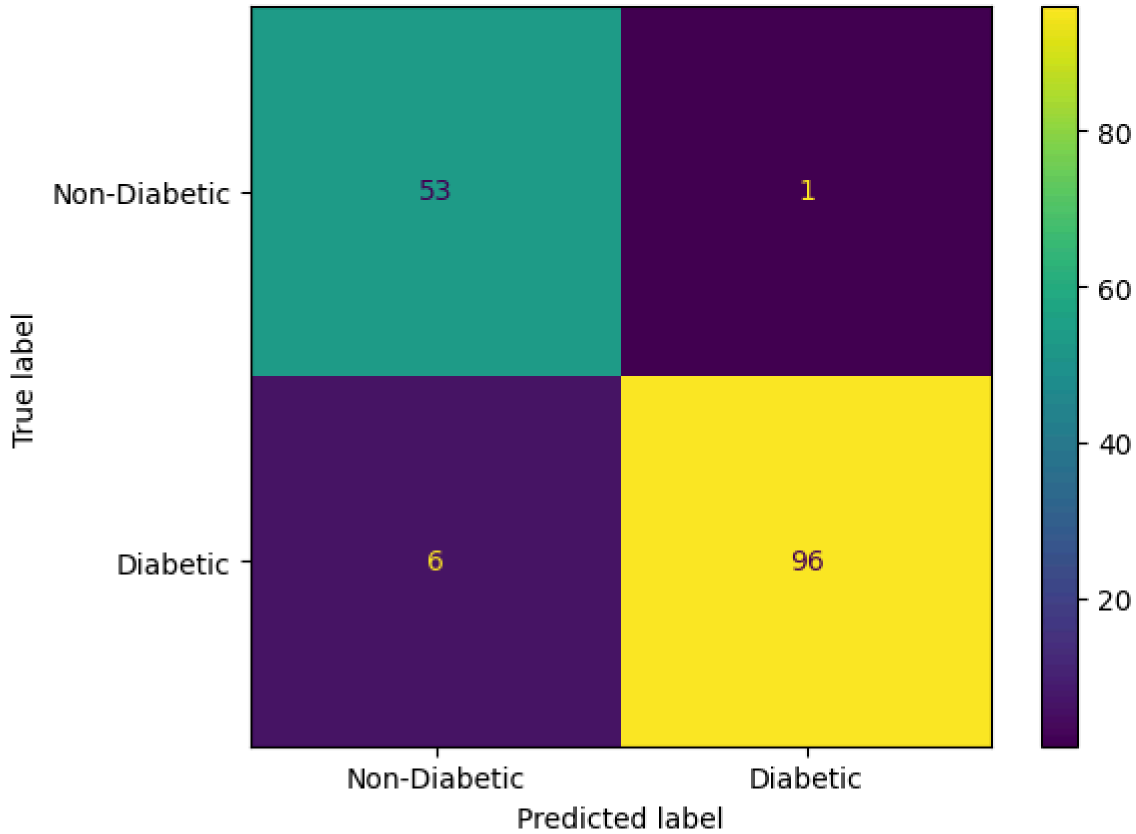
```
              precision    recall  f1-score   support

 Negative(0)       0.90      0.98      0.94        54
 Positive(1)       0.99      0.94      0.96       102

    accuracy                           0.96       156
   macro avg       0.94      0.96      0.95       156
weighted avg       0.96      0.96      0.96       156
```

In [74]:
```
# Save the classification report to csv file
clf_report=classification_report(y_test, y_pred_dt_depth5, target_names=target_n
report_df = pd.DataFrame(clf_report).transpose()
report_df.to_csv("model_evaluation/decision_tree/dt_clf_report.csv")
```

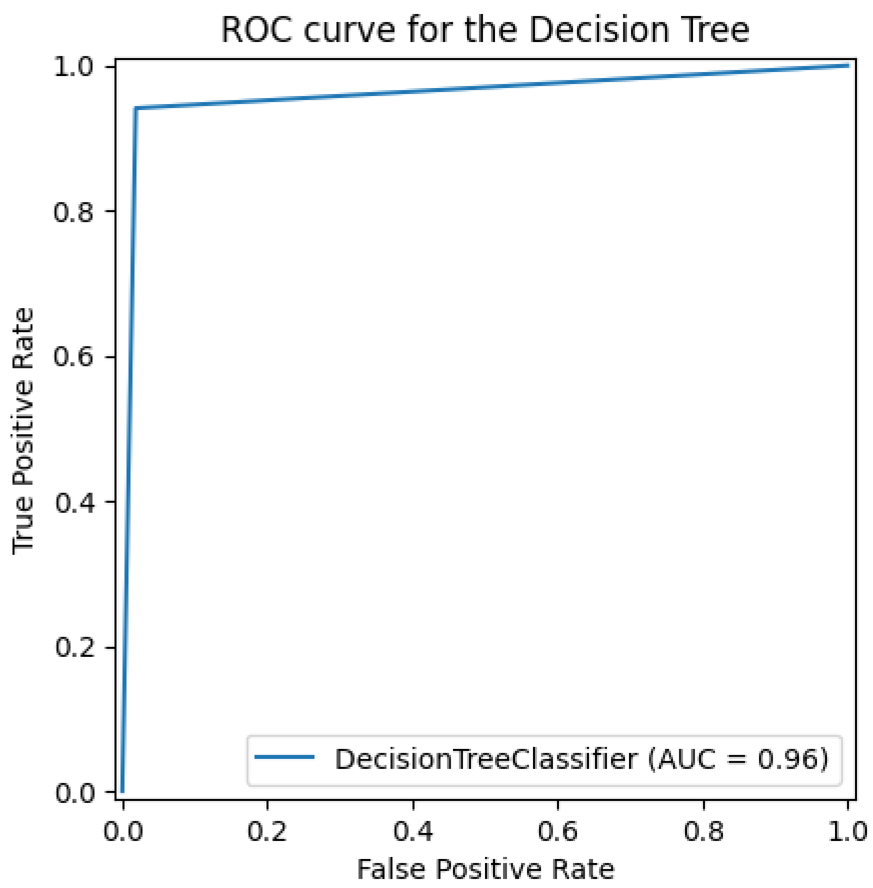
In [75]:
```
# Confusion Matrix
conf_matrix=confusion_matrix(y_test, y_pred_dt_depth5)
print(conf_matrix)
```

```
[[53  1]
 [ 6 96]]
```

In [76]:
```
# Plot confusion matrix (Decision Tree model)
conf_matrix_display=ConfusionMatrixDisplay(conf_matrix, display_labels = ["Non-D
conf_matrix_display.plot()
plt.savefig('model_evaluation/decision_tree/dt_confusion_matrix.png', dpi=100, b
plt.show()
```



In [77]:
```
# Plot ROC Curve for Decision Tree Classifier model
fpr, tpr, threshold = roc_curve(y_test, y_pred_dt_depth5)
roc_auc = auc(fpr, tpr)
roc_display = RocCurveDisplay(fpr=fpr, tpr=tpr)
roc_display.plot(label='DecisionTreeClassifier (AUC = %.2f)' % roc_auc)
plt.savefig('model_evaluation/decision_tree/dt_roc_curve.png', dpi=100, bbox_inc
plt.title("ROC curve for the Decision Tree")
plt.show()
```



In [78]:
```
# K-Fold Cross Validation (K=5)
kfold = KFold(n_splits=5, shuffle=True, random_state=42)
scores = cross_val_score(dt_model_depth5, X, y, scoring='accuracy', cv=kfold)
print("Cross validation scores:\n", scores)
print("Mean Accuracy: ", scores.mean())
print("Standard Deviation: ", scores.std())
```

```
Cross validation scores:
 [0.95192308 0.95192308 0.96153846 0.94230769 0.97115385]
Mean Accuracy:  0.9557692307692307
Standard Deviation:  0.009805806756909214
```

Exploring how the Decision Tree Classifier works under the hood

In [80]:
```
# Create Decision Tree Plot
from IPython.display import Image
from sklearn import tree
import pydotplus
```

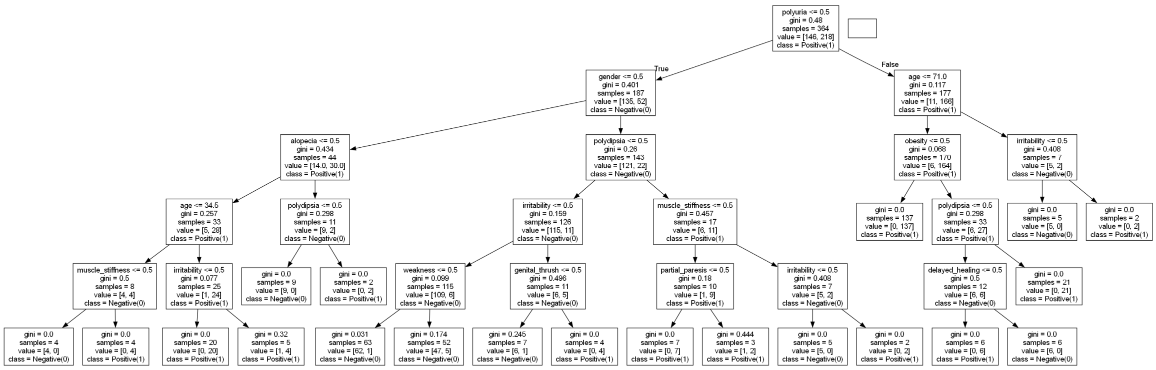
In [81]:
```
feature_names = X.columns
```

In [82]:
```
# Create a Dot Plot
dot_data = tree.export_graphviz(dt_model_depth5, out_file=None, feature_names=fe
```

In [83]:
```
# Draw a graph
graph = pydotplus.graph_from_dot_data(dot_data)
```

In [84]:
```
Image(graph.create_png())
```

Out[84]:



In [85]:

```python
# Save the plot
graph.write_png("decision_tree_diagram_for_diabetes_prediction.png")
```

Out[85]:

```
True
```

Random Forest Model

In [86]:

```python
# Create Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier

forest = RandomForestClassifier(n_estimators=70, random_state=42)
forest.fit(x_train, y_train)

print("Training accuracy: ", forest.score(x_train, y_train))
print("Testing accuracy: ", forest.score(x_test, y_test))
```

```
Training accuracy:  1.0
Testing accuracy:  0.9935897435897436
```

In [87]:

```python
# Prediction of the Random Forest model on the test dataset (first 10 rows)
forest.predict(x_test[0:10])
```

Out[87]:

```
array([0, 1, 1, 1, 1, 1, 1, 0, 1, 0])
```

In [88]:

```python
# Prediction probability of the above samples
forest_prob=forest.predict_proba(x_test[0:10])
for i, prob in enumerate(forest_prob):
    print(f"Sample {i+1}: Class 0 Probability = {prob[0]:.3f}, Class 1 Probabili
```

```
Sample 1: Class 0 Probability = 0.986, Class 1 Probability = 0.014
Sample 2: Class 0 Probability = 0.014, Class 1 Probability = 0.986
Sample 3: Class 0 Probability = 0.014, Class 1 Probability = 0.986
Sample 4: Class 0 Probability = 0.071, Class 1 Probability = 0.929
Sample 5: Class 0 Probability = 0.014, Class 1 Probability = 0.986
Sample 6: Class 0 Probability = 0.000, Class 1 Probability = 1.000
Sample 7: Class 0 Probability = 0.014, Class 1 Probability = 0.986
Sample 8: Class 0 Probability = 0.614, Class 1 Probability = 0.386
Sample 9: Class 0 Probability = 0.414, Class 1 Probability = 0.586
Sample 10: Class 0 Probability = 1.000, Class 1 Probability = 0.000
```

In [89]:

```python
# Classification report for our Random Forest model
y_pred_forest = forest.predict(x_test)
print(classification_report(y_test, y_pred_forest, target_names=target_names))
```

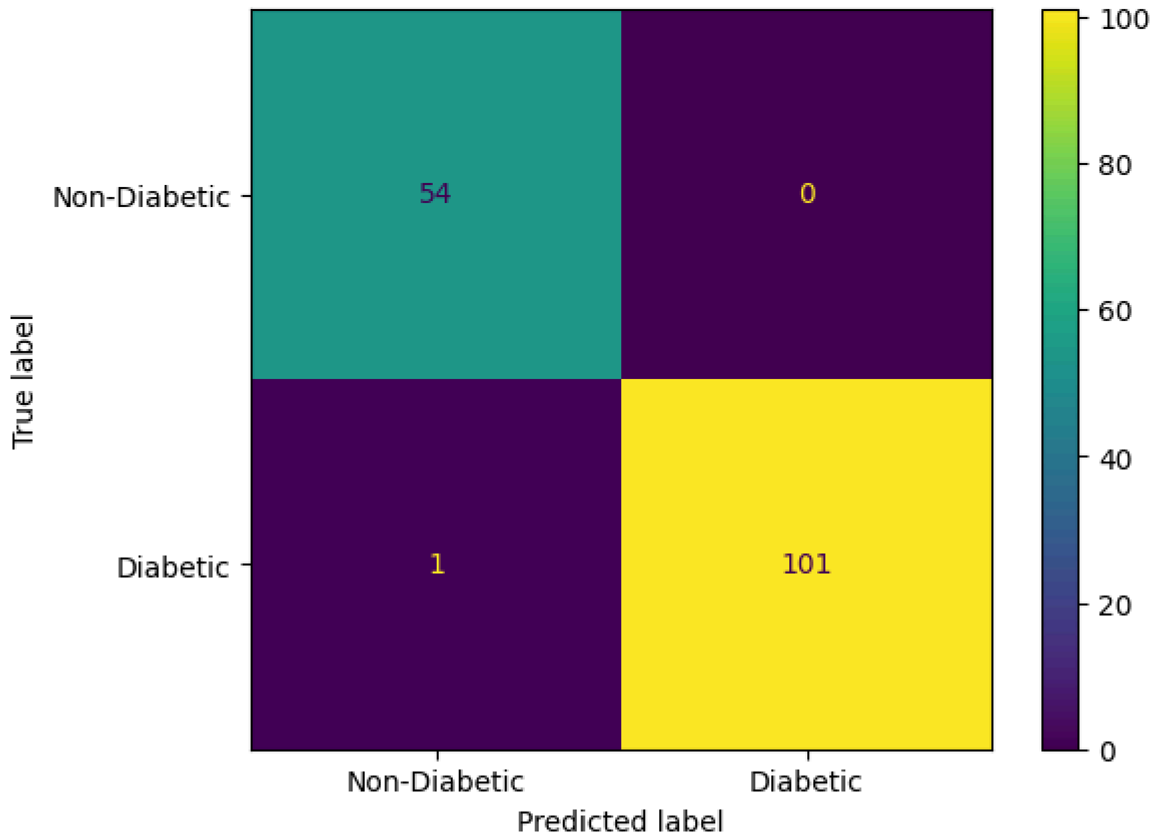
```
              precision    recall  f1-score   support

 Negative(0)       0.98      1.00      0.99        54
 Positive(1)       1.00      0.99      1.00       102

    accuracy                           0.99       156
   macro avg       0.99      1.00      0.99       156
weighted avg       0.99      0.99      0.99       156
```

In [90]:
```
# Save the classification report to csv file
clf_report=classification_report(y_test, y_pred_forest, target_names=target_name
report_df = pd.DataFrame(clf_report).transpose()
report_df.to_csv("model_evaluation/random_forest/rf_clf_report.csv")
```

In [91]:
```
# Confusion Matrix
conf_matrix=confusion_matrix(y_test, y_pred_forest)
print(conf_matrix)
```

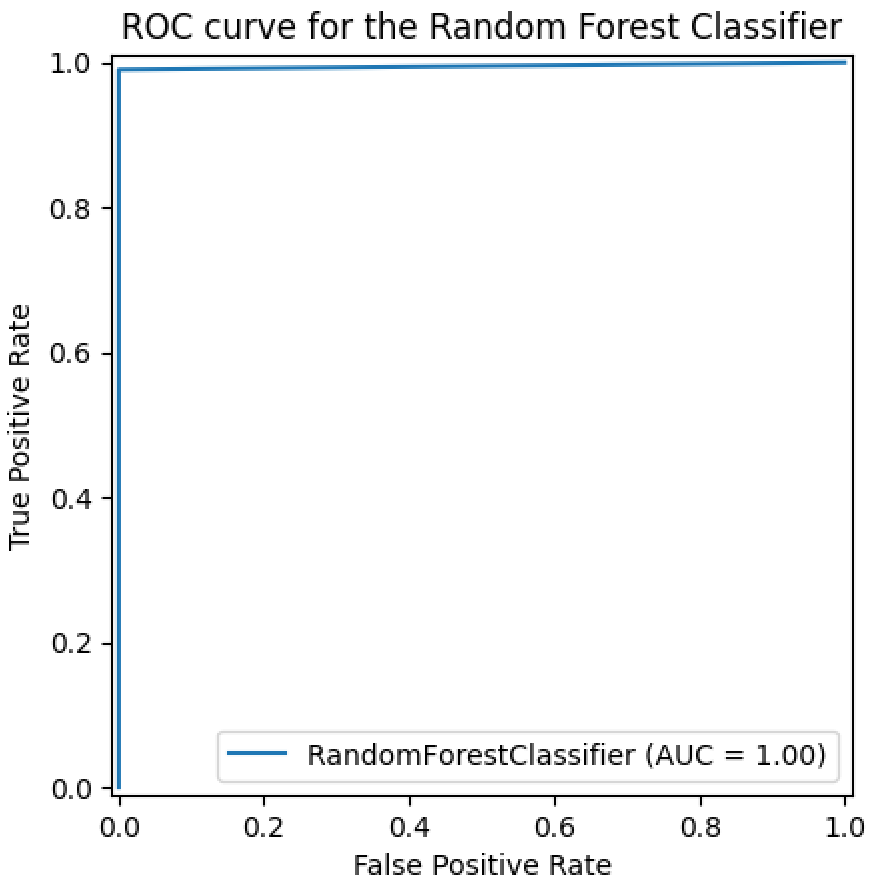
```
[[ 54   0]
 [  1 101]]
```

In [92]:
```
# Plot confusion matrix (Random Forest)
conf_matrix_display=ConfusionMatrixDisplay(conf_matrix, display_labels = ["Non-D
conf_matrix_display.plot()
plt.savefig('model_evaluation/random_forest/rf_confusion_matrix.png', dpi=100, b
plt.show()
```



In [93]:
```
# Plot ROC Curve for Random Forest Classifier model
fpr, tpr, threshold = roc_curve(y_test, y_pred_forest)
roc_auc = auc(fpr, tpr)
roc_display = RocCurveDisplay(fpr=fpr, tpr=tpr)
roc_display.plot(label='RandomForestClassifier (AUC = %.2f)' % roc_auc)
plt.savefig('model_evaluation/random_forest/rf_roc_curve.png', dpi=100, bbox_inc
```

```python
plt.title("ROC curve for the Random Forest Classifier")
plt.show()
```



In [94]:
```python
# K-Fold Cross Validation (K=5)
kfold = KFold(n_splits=5, shuffle=True, random_state=42)
scores = cross_val_score(forest, X, y, scoring='accuracy', cv=kfold)
print("Cross validation scores:\n", scores)
print("Mean Accuracy: ", scores.mean())
print("Standard Deviation: ", scores.std())
```

```
Cross validation scores:
 [0.99038462 0.97115385 0.97115385 0.98076923 0.99038462]
Mean Accuracy:  0.9807692307692308
Standard Deviation:  0.008600261451922287
```

Support Vector Machine Model

In [95]:
```python
# Create the optimal SVC model using hyperparameter tuning
from sklearn.svm import SVC

param_grid = {
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'gamma': [0.001, 0.01, 0.1, 1, 10, 100]

}
kfold = KFold(n_splits=5, shuffle=True, random_state=42)
svc_grid = GridSearchCV(SVC(probability=True), param_grid, cv=kfold, verbose=Tru
svc_grid.fit(x_train, y_train)
y_pred_svc_grid = svc_grid.predict(x_test)

print("Training set score: ", svc_grid.score(x_train, y_train))
print("Test Set Score: ",svc_grid.score(x_test, y_test))
```

```
print("Best parameters: ", svc_grid.best_params_)
print("Best cross validation score: {:.2f}".format(svc_grid.best_score_))
print("Best estimator: ", svc_grid.best_estimator_)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
Training set score:  1.0
Test Set Score:  0.9743589743589743
Best parameters:  {'C': 100, 'gamma': 0.1}
Best cross validation score: 0.94
Best estimator:  SVC(C=100, gamma=0.1, probability=True)
```

In [96]:
```
# Prediction of the Support Vector Classifier model on the test dataset (first 1
svc_grid.predict(x_test[0:10])
```

Out[96]:
```
array([0, 1, 1, 1, 1, 1, 1, 0, 1, 0])
```

In [97]:
```
# Prediction probability of the above samples
svc_prob=svc_grid.predict_proba(x_test[0:10])
for i, prob in enumerate(svc_prob):
    print(f"Sample {i+1}: Class 0 Probability = {prob[0]:.3f}, Class 1 Probabili
```

```
Sample 1: Class 0 Probability = 0.936, Class 1 Probability = 0.064
Sample 2: Class 0 Probability = 0.004, Class 1 Probability = 0.996
Sample 3: Class 0 Probability = 0.015, Class 1 Probability = 0.985
Sample 4: Class 0 Probability = 0.017, Class 1 Probability = 0.983
Sample 5: Class 0 Probability = 0.017, Class 1 Probability = 0.983
Sample 6: Class 0 Probability = 0.005, Class 1 Probability = 0.995
Sample 7: Class 0 Probability = 0.021, Class 1 Probability = 0.979
Sample 8: Class 0 Probability = 0.586, Class 1 Probability = 0.414
Sample 9: Class 0 Probability = 0.103, Class 1 Probability = 0.897
Sample 10: Class 0 Probability = 0.936, Class 1 Probability = 0.064
```

In [98]:
```
# Classification report for our Support Vector Classifier model
y_pred_svc_grid = svc_grid.predict(x_test)
print(classification_report(y_test, y_pred_svc_grid, target_names=target_names))
```

```
              precision    recall  f1-score   support

 Negative(0)       0.96      0.96      0.96        54
 Positive(1)       0.98      0.98      0.98       102

    accuracy                           0.97       156
   macro avg       0.97      0.97      0.97       156
weighted avg       0.97      0.97      0.97       156
```

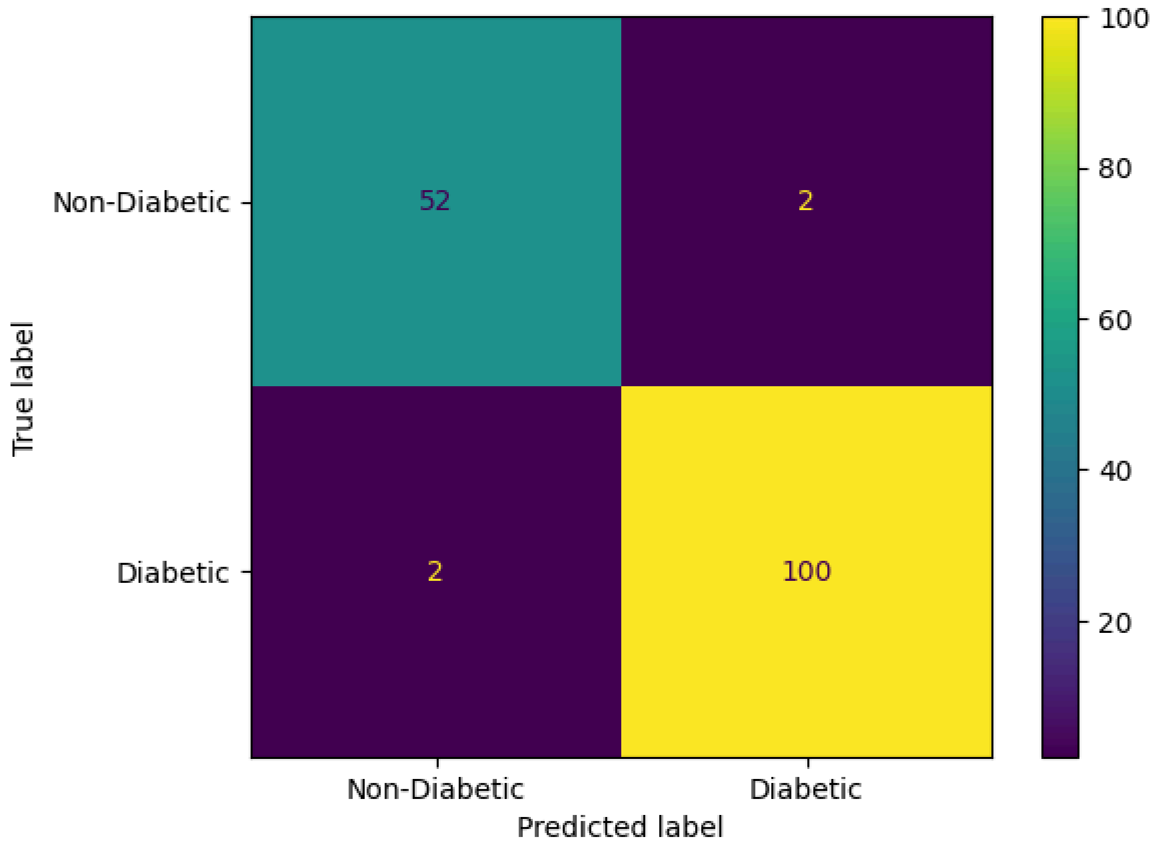
In [99]:
```
# Save the classification report to csv file
clf_report=classification_report(y_test, y_pred_svc_grid, target_names=target_na
report_df = pd.DataFrame(clf_report).transpose()
report_df.to_csv("model_evaluation/support_vector_classifier/svc_clf_report.csv"
```

In [100…
```
# Confusion Matrix
conf_matrix=confusion_matrix(y_test, y_pred_svc_grid)
print(conf_matrix)
```

```
[[ 52   2]
 [  2 100]]
```

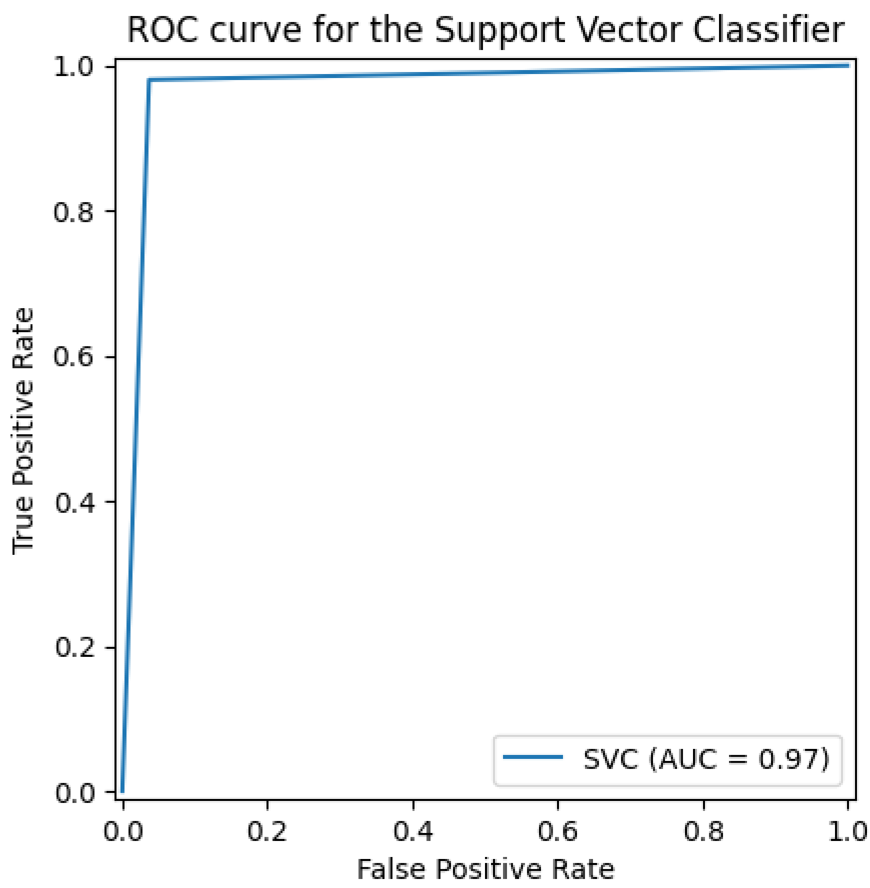
In [101…
```
# Plot confusion matrix for Support Vector Classifier model
conf_matrix_display=ConfusionMatrixDisplay(conf_matrix, display_labels = ["Non-D
```

```
conf_matrix_display.plot()
plt.savefig('model_evaluation/support_vector_classifier/svc_confusion_matrix.png
plt.show()
```



In [102…

```
# Plot ROC Curve for Support Vector Classifier model
fpr, tpr, threshold = roc_curve(y_test, y_pred_svc_grid)
roc_auc = auc(fpr, tpr)
roc_display = RocCurveDisplay(fpr=fpr, tpr=tpr)
roc_display.plot(label='SVC (AUC = %.2f)' % roc_auc)
plt.savefig('model_evaluation/support_vector_classifier/svc_roc_curve.png', dpi=
plt.title("ROC curve for the Support Vector Classifier")
plt.show()
```



In [103…

```
# Cross Validation values of Support Vector Classifier model
# Get the index of the best estimator
best_index = svc_grid.best_index_

# Extract scores for the best estimator
best_cv_scores = svc_grid.cv_results_["split0_test_score"][best_index], \
                 svc_grid.cv_results_["split1_test_score"][best_index], \
                 svc_grid.cv_results_["split2_test_score"][best_index], \
                 svc_grid.cv_results_["split3_test_score"][best_index], \
                 svc_grid.cv_results_["split4_test_score"][best_index]

best_cv_scores = [float(score) for score in best_cv_scores]
mean_test_score = svc_grid.cv_results_["mean_test_score"][best_index]
std_test_score = svc_grid.cv_results_["std_test_score"][best_index]

print("Best Index: ", best_index)
print("Best Estimator: ", svc_grid.best_estimator_)
print("Cross-validation scores of the best estimator:", best_cv_scores)
print("Mean accuracy:", mean_test_score)
print("Standard deviation:", std_test_score)
```

```
Best Index:  32
Best Estimator:  SVC(C=100, gamma=0.1, probability=True)
Cross-validation scores of the best estimator: [0.9452054794520548, 0.90410958904
10958, 0.958904109589041, 0.9041095890410958, 1.0]
Mean accuracy: 0.9424657534246574
Standard deviation: 0.036139468378829934
```

In [104…

```
# Compare models using F1 score
from sklearn.metrics import f1_score
f1_score_lr_model = f1_score(y_test, y_pred_lr_grid_search)
f1_score_dt_model = f1_score(y_test, y_pred_dt_depth5)
```

```
f1_score_random_forest_model = f1_score(y_test, y_pred_forest)
f1_score_svc_model = f1_score(y_test, y_pred_svc_grid)
```

In [105…

```
print("F1 Score for Logistic Regression Model: ", f1_score_lr_model)
print("F1 Score for Decision Tree Model: ", f1_score_dt_model)
print("F1 Score for Random Forest Model: ", f1_score_random_forest_model)
print("F1 Score for Support Vector Classifier Model: ", f1_score_svc_model)
```

```
F1 Score for Logistic Regression Model:  0.945273631840796
F1 Score for Decision Tree Model:  0.964824120603015
F1 Score for Random Forest Model:  0.9950738916256158
F1 Score for Support Vector Classifier Model:  0.9803921568627451
```

Narrative

- The Random Forest Classifier model has the highest F1 Score

Save the models using Joblib

In [106…

```
import joblib
```

In [118…

```
# Save the Logistic Regression model
lr_grid_model_file = open("models/logistic_regression_model_grid_search_new.pkl"
joblib.dump(lr_grid_search, lr_grid_model_file)
lr_grid_model_file.close()
```

In [119…

```
# Save the Decision Tree model
dt_model_file = open("models/decision_tree_model_depth_5.pkl", "wb")
joblib.dump(dt_model_depth5, dt_model_file)
dt_model_file.close()
```

In [120…

```
# Save the Random Forest model
forest_model_file = open("models/random_forest_model.pkl", "wb")
joblib.dump(forest, forest_model_file)
forest_model_file.close()
```

In [121…

```
# Save the Support Vector Classifier model
svc_grid_model_file = open("models/svc_grid_model_final.pkl", "wb")
joblib.dump(svc_grid, svc_grid_model_file)
svc_grid_model_file.close()
```