DIABETES PREDICTION SYSTEM

Project Submission Part -5

Introduction :

- Diabetes is a chronic metabolic disorder characterized by high levels of blood sugar, leading to various health complications if not managed effectively. Early diagnosis and timely intervention are crucial in mitigating the risks associated with diabetes. The primary goal of this documentation is to address the problem of diabetes prediction using machine learning techniques. We aim to develop predictive models that

can analyze a set of patient attributes and accurately classify individuals into diabetic and non-diabetic groups.

- Machine learning and data analytics techniques have shown promise in predicting the risk of diabetes in individuals. By analyzing relevant medical and lifestyle data, it is possible to develop predictive models that can identify individuals at high risk of developing diabetes. These models can provide valuable insights to healthcare professionals and individuals, enabling them to take proactive steps in preventing or managing the disease.
- The importance of predicting diabetes cannot be overstated. Diabetes is a global health concern affecting millions of people, and its prevalence continues to rise. It leads to severe health complications, including heart disease, kidney failure, and vision impairment. By developing accurate diabetes prediction models

Content for project :

In this project we will document our project and make it well prepare for the submission

In documentation we will clearly outline the problem statement and describe the dataset used.

Begin by clearly defining the problem you are addressing in your project. Explain the context, the

business or research problem, and why it is important to solve. For example, "Our project aims with AI Based Diabetes System."

Data Source :

A good data source of diabetes prediction using machine learning should be Accurate , Complete , Covering the physical details , Accessible

Data Source Link : https://www.kaggle.com/datasets/mathchi/diabetes-data-set

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome	Pregnancies
0	6	148	72	35	0	33.6	0.627	50	1	6
1	1	85	66	29	0	26.6	0.351	31	0	1
2	8	183	64	0	0	23.3	0.672	32	1	8

3	1	89	66	23	94	28.1	0.167	21	0	1
4	0	137	40	35	168	43.1	2.288	33	1	0
5	5	116	74	0	0	25.6	0.201	30	0	5
6	3	78	50	32	88	31	0.248	26	1	3
7	10	115	0	0	0	35.3	0.134	29	0	10
8	2	197	70	45	543	30.5	0.158	53	1	2
9	8	125	96	0	0	0	0.232	54	1	8
10	4	110	92	0	0	37.6	0.191	30	0	4
11	10	168	74	0	0	38	0.537	34	1	10
12	10	139	80	0	0	27.1	1.441	57	0	10
13	1	189	60	23	846	30.1	0.398	59	1	1
14	5	166	72	19	175	25.8	0.587	51	1	5
15	7	100	0	0	0	30	0.484	32	1	7
16	0	118	84	47	230	45.8	0.551	31	1	0
17	7	107	74	0	0	29.6	0.254	31	1	7
18	1	103	30	38	83	43.3	0.183	33	0	1
19	1	115	70	30	96	34.6	0.529	32	1	1
20	3	126	88	41	235	39.3	0.704	27	0	3
21	8	99	84	0	0	35.4	0.388	50	0	8
22	7	196	90	0	0	39.8	0.451	41	1	7
23	9	119	80	35	0	29	0.263	29	1	9
24	11	143	94	33	146	36.6	0.254	51	1	11
25	10	125	70	26	115	31.1	0.205	41	1	10
26	7	147	76	0	0	39.4	0.257	43	1	7
27	1	97	66	15	140	23.2	0.487	22	0	1
28	13	145	82	19	110	22.2	0.245	57	0	13

Data Collection and Preprocessing :

- Describe the data sources and types used for this project (e.g., medical records, surveys, publicly available datasets).
- Explain the data collection process, including ethical considerations.
- Detail the steps taken to clean and prepare the data for analysis.

- Address missing data, outliers, and any data transformation techniques used.

Exploratory Data Analysis :

- Present summary statistics and visualizations to better understand the dataset.
- Identify potential correlations and patterns related to diabetes.

Feature Engineering :

- Present summary statistics and visualizations to better understand the dataset.
- Identify potential correlations and patterns related to diabetes.

Advanced Regression Technique :

Ridge Regression:

- Ridge regression adds a regularization term to the linear regression equation, which helps prevent overfitting by penalizing large coefficient values.

➢ Lasso Regression:

- Lasso regression is similar to ridge regression but uses L1 regularization. It not only prevents overfitting but also performs feature

selection by driving some coefficients to exactly zero.

- **Elastic Net Regression:**
  - Elastic Net combines L1 (Lasso) and L2 (Ridge) regularization techniques, striking a balance between feature selection and coefficient shrinkage.
- **Polynomial Regression:**
  - Polynomial regression allows for modeling non-linear relationships between predictors and the target variable.
- **Support Vector Regression (SVR):**
  - SVR is a regression technique based on support vector machines (SVMs).
- **Random Forest Regression:**
  - Random Forest is an ensemble learning method that combines multiple decision trees to make predictions.

Model Selection

- Describe the machine learning models considered for diabetes prediction.
- Explain the criteria for selecting the final model(s).

Model Development

- Detail the process of training and fine-tuning the selected model(s).
- Discuss hyperparameter tuning and cross-validation techniques.

Model Evaluation

- Present the metrics used to evaluate the model's performance (e.g., accuracy, precision, recall, F1-score, ROC-AUC).
- Provide the results of model evaluation on the test dataset.

Program :

Diabetes Prediction:

```
importnumpyasnp
import pandas aspd
importseabornassns
importmatplotlib.pyplotasplt
importplotly.expressaspx
# open Data set

df=pd.read_csv('/kaggle/input/diabetes-data-set/diabetes.csv')
```

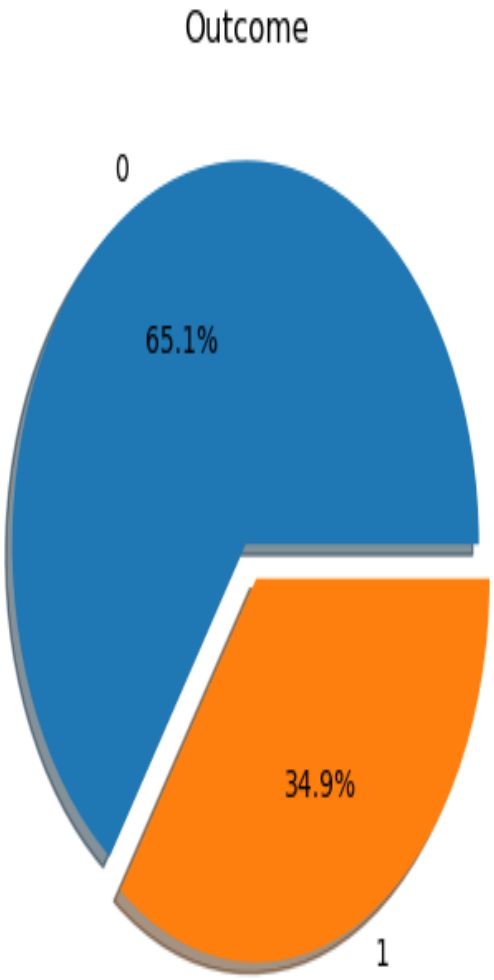
Data Visualization :

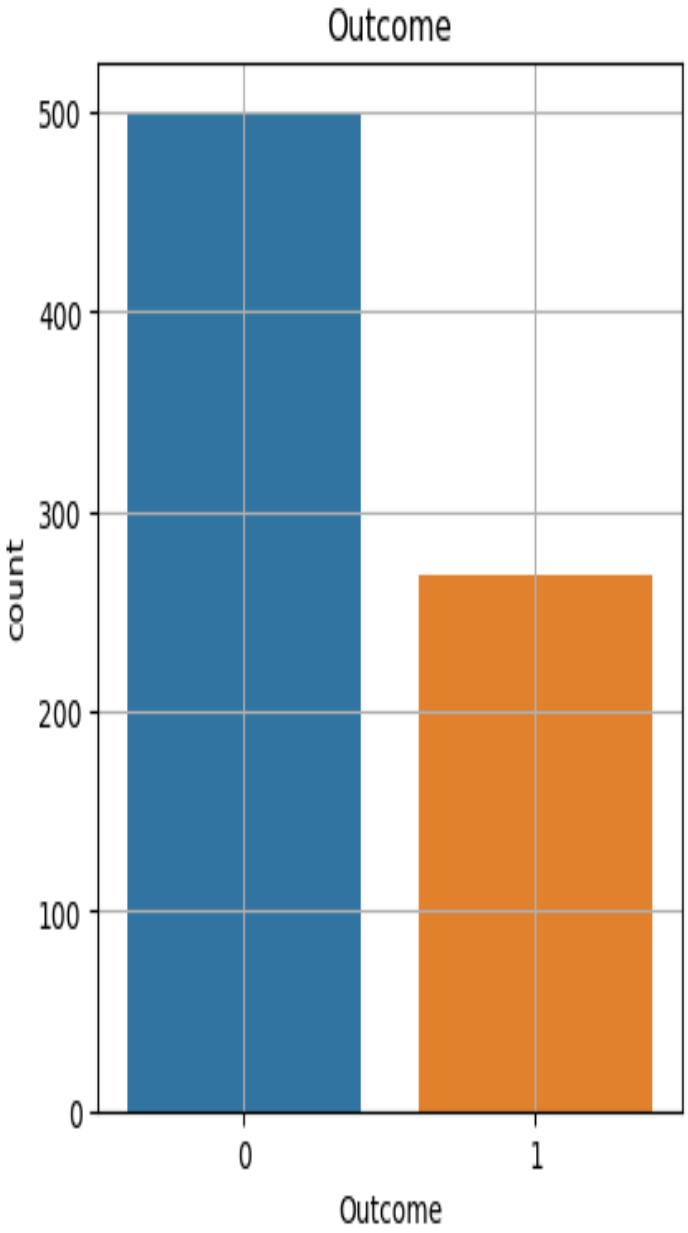
```
ln[08]
```

f, ax = plt.subplots(1, 2, figsize=(10, 5))

```
df['Outcome'].value_counts().plot.pie(explode=[0, 0.1], autopct='%1.1f%%', ax=ax[0], shadow=True)

ax[0].set_title('Outcome')

ax[0].set_ylabel(' ')

sns.countplot(x='Outcome', data=df, ax=ax[1])  # Use 'x' instead of 'Outcome'

ax[1].set_title('Outcome')

N, P = df['Outcome'].value_counts()

print('Negative (0):', N)

print('Positive (1):', P)

plt.grid()

plt.show()
```

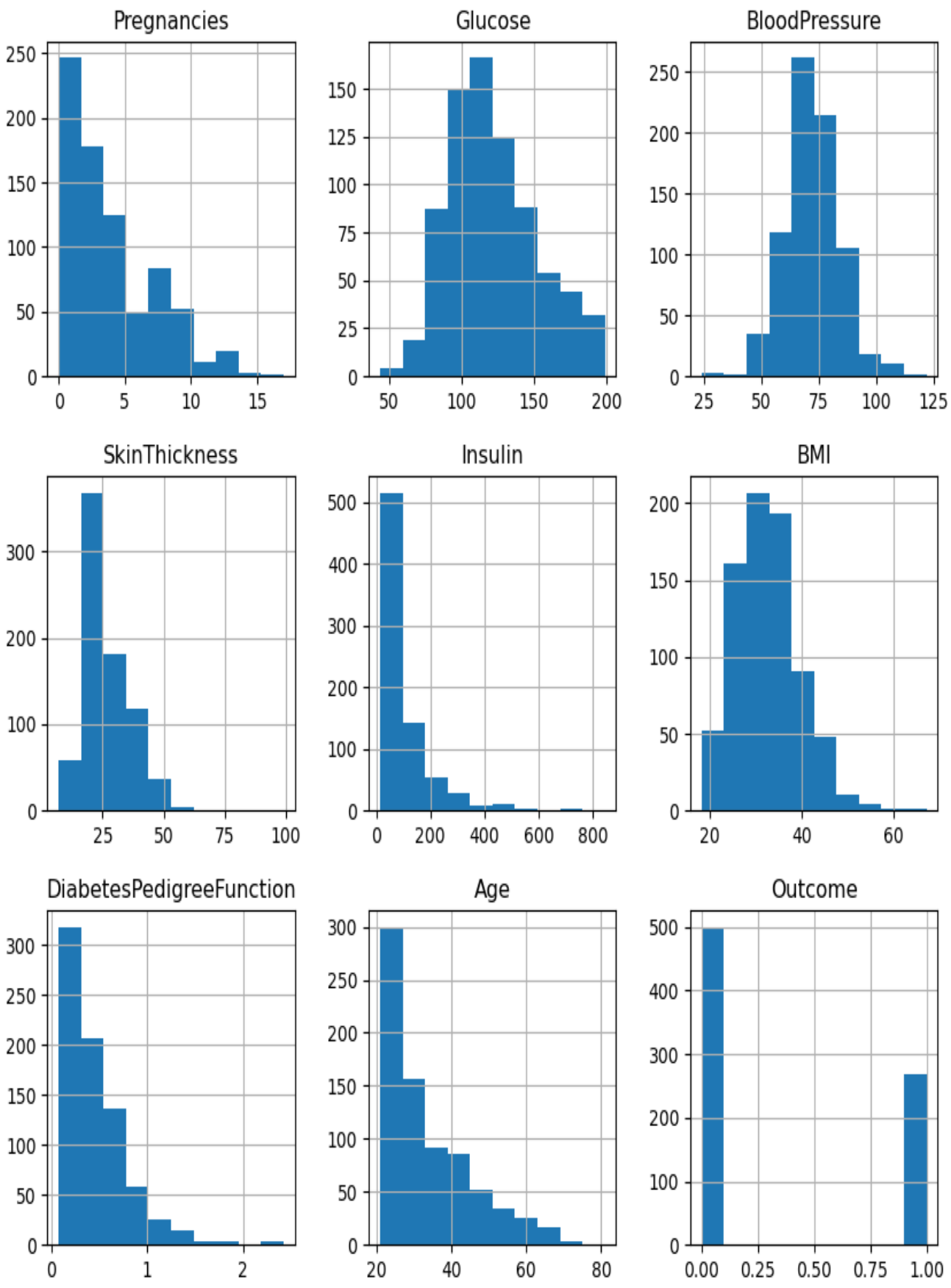
```
Negative (0): 500
Positive (1): 268
```





Histograms :

```
ln[ 21]:
df.hist(bins=10, figsize=(10, 10))
plt.show()
```


Pregnancies
Glucose
BloodPressure
SkinThickness
Insulin
BMI
DiabetesPedigreeFunction
Age
Outcome

Linear Regression :

```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(solver='liblinear',
multi_class='ovr')
lr.fit(X_train, y_train)
```

out[]

```
LogisticRegression
LogisticRegression(multi_class='ovr', solver='liblinear')
```

Decision Tree :

```
from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier()
dt.fit(X_train, y_train)
```

out[]

```
DecisionTreeClassifier
DecisionTreeClassifier()
```

Making Prediction :

#logistic regression

```
X_test.shape
Out[]
(154, 8)
ln[]
lr_pred=lr.predict(X_test)
lr_pred.shape
out[]
(154,)
```

#Decision Tree

```
dt_pred=dt.predict(X_test)
dt_pred.shape
out[]
(154,)
```

Model Evaluation :

```
from sklearn.metrics import accuracy_score
```

```
print("Train Accuracy of Logistic Regression: ",
lr.score(X_train, y_train)*100)

print("Accuracy (Test) Score of Logistic Regression:
", lr.score(X_test, y_test)*100)

print("Accuracy Score of Logistic Regression: ",
accuracy_score(y_test, lr_pred)*100)


out[]

Train Accuracy of Logistic Regression:
77.36156351791531

Accuracy (Test) Score of Logistic Regression:
77.27272727272727

Accuracy Score of Logistic Regression:
77.27272727272727


#for decision tree


print("Train Accuracy of Decesion Tree: ",
dt.score(X_train, y_train)*100)

print("Accuracy (Test) Score of Decesion Tree: ",
dt.score(X_test, y_test)*100)

print("Accuracy Score of Decesion Tree: ",
accuracy_score(y_test, dt_pred)*100)


out[]


Train Accuracy of Decesion Tree:  100.0
```

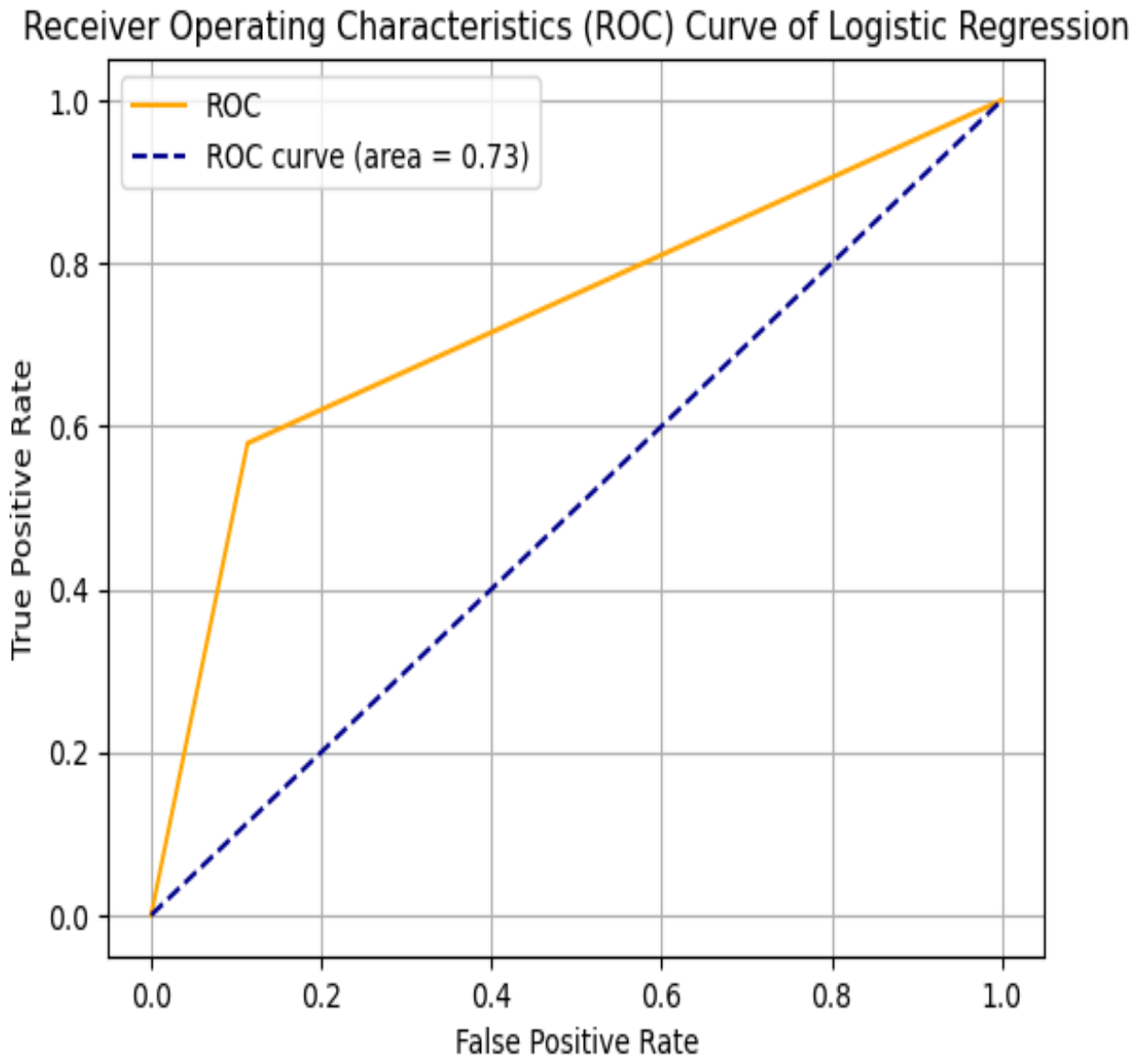
```
Accuracy (Test) Score of Decesion Tree:
80.51948051948052

Accuracy Score of Decesion Tree:  80.51948051948052
```

ROC Curve & ROC AUC :

```
# Area under Curve:

auc= roc_auc_score(y_test, lr_pred)

print("ROC AUC SCORE of logistic Regression is ",
auc)


out[]


ROC AUC SCORE of logistic Regression is
0.7327726532826913


ln[]

from sklearn.metrics import roc_curve, auc

import matplotlib.pyplot as plt

fpr, tpr, thresholds = roc_curve(y_test, lr_pred)

plt.plot(fpr, tpr, color='orange', label="ROC")

plt.plot([0, 1], [0, 1], color='darkblue',
linestyle='--', label='ROC curve (area = %0.2f)' %
auc(fpr, tpr))

plt.xlabel("False Positive Rate")

plt.ylabel("True Positive Rate")
```

```
plt.title("Receiver Operating Characteristics (ROC)
Curve of Logistic Regression")
plt.legend()
plt.grid()
plt.show()
```

out[ ]



Conclusion :

In this documentation, we have explored the process of diabetes prediction using machine learning, from data collection and preprocessing to model selection and deployment. The development of predictive models for diabetes has significant implications for healthcare, and our work here serves as a valuable guide for those seeking to make a positive impact in this domain.

We've learned that accurate diabetes prediction is not only feasible but also crucial for several reasons. Early intervention, optimized healthcare resource allocation, and personalized preventive care are just a few of the benefits that come with successfully predicting diabetes. By leveraging data and machine learning, we can empower healthcare professionals and individuals to take proactive steps in managing this chronic condition.