Exploratory Data Analysis (EDA) on Diabetes Dataset

This notebook performs a complete EDA on a diabetes dataset to understand key health indicators, detect missing values and outliers, visualize important trends, and prepare the data for further modeling or analysis.

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1. Import Required Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2. Load the Dataset

```
diabetes_data = pd.read_csv("diabetes_data.csv")
diabetes_data.head()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

```
diabetes_data.tail()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

3. Basic Information About the Dataset

```
diabetes_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

4. Dataset Shape and Columns

```
print("Shape:", diabetes_data.shape)
print("Columns:", diabetes_data.columns.values)
```

```
Shape: (768, 9)
Columns: ['Pregnancies' 'Glucose' 'BloodPressure' 'SkinThickness' 'Insulin'
 'BMI' 'DiabetesPedigreeFunction' 'Age' 'Outcome']
```

5. Mean and Median of Age, Blood Pressure, and BMI

```
print("Mean Values:")
print("Age:", diabetes_data['Age'].mean())
print("BloodPressure:", diabetes_data['BloodPressure'].mean())
print("BMI:", diabetes_data['BMI'].mean())

print("\nMedian Values:")
print("Age:", diabetes_data['Age'].median())
print("BloodPressure:", diabetes_data['BloodPressure'].median())
print("BMI:", diabetes_data['BMI'].median())
```

```
Mean Values:
Age: 33.240885416666664
BloodPressure: 69.10546875
BMI: 31.992578124999998

Median Values:
Age: 29.0
BloodPressure: 72.0
BMI: 32.0
```

6. Descriptive Statistics

```
diabetes_data.describe()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	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	0.471876	33.240885	0.348958
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

7. Check for Missing Values

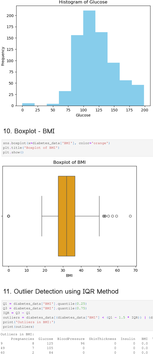
```
diabetes_data.isnull().sum()
```

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

8. Bar Plot - Diabetes Outcome Count

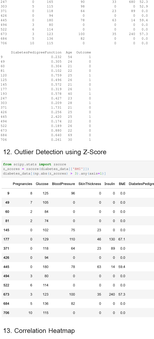
```
sns.countplot(x='Outcome', data=diabetes_data, palette='Set2')
plt.title('Distribution of Diabetes Outcome')
plt.show()
```

```
C:\Users\Sanjay\AppData\Local\Temp\ipykernel_24492\3161922795.py:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(x='Outcome', data=diabetes_data, palette='Set2')
```



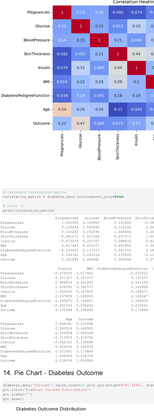
9. Histogram - Glucose Levels

```
plt.hist(diabetes_data['Glucose'], bins=15, color='skyblue')
plt.title('Histogram of Glucose')
plt.xlabel('Glucose')
plt.ylabel('Frequency')
plt.show()
```



10. Boxplot - BMI

```
sns.boxplot(x=diabetes_data['BMI'], color='orange')
plt.title('Boxplot of BMI')
plt.show()
```



11. Outlier Detection using IQR Method

```
Q1 = diabetes_data['BMI'].quantile(0.25)
Q3 = diabetes_data['BMI'].quantile(0.75)
IQR = Q3 - Q1
outliers = diabetes_data[(diabetes_data['BMI'] < Q1 - 1.5 * IQR) | (diabetes_data['BMI'] > Q3 + 1.5 * IQR)]
print("Outliers in BMI:")
print(outliers)
```

```
Outliers in BMI:
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin  BMI  \
9            8      125             96              0        0  0.0
49           7      105              0              0        0  0.0
60           2       84              0              0        0  0.0
81           2       74              0              0        0  0.0
145          0      102             75             23        0  0.0
177          0      129            110             46      130  67.1
303          2       92             76             20        0  24.2
332          1      128              0              0        0  0.0
371          0      118             64             23       89  0.0
426          0       94              0              0        0  0.0
445          0      180             78             63       14  59.4
673          3      123            100             35      240  57.3
691          8      187             76             30        0  0.0
704          10     115              0              0        0  0.0

     DiabetesPedigreeFunction  Age  Outcome
9                       0.232   54        1
49                      0.305   24        0
60                      0.304   21        0
81                      0.102   22        0
145                     0.082   21        0
177                     0.314   43        1
371                     0.279   21        0
426                     0.256   25        0
445                     2.420   25        1
673                     0.880   22        0
691                     0.904   26        0
704                     0.261   30        1
```

12. Outlier Detection using Z-Score

```
from scipy.stats import zscore
z_scores = zscore(diabetes_data['BMI'])
diabetes_data['bmi_outlier'] = (z_scores > 3).astype(int)
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin  BMI  \
9            8      125             96              0        0  0.0
49           7      105              0              0        0  0.0
60           2       84              0              0        0  0.0
81           2       74              0              0        0  0.0
145          0      102             75             23        0  0.0
177          0      129            110             46      130  67.1
303          2       92             76             20        0  24.2
332          1      128              0              0        0  0.0
371          0      118             64             23       89  0.0
426          0       94              0              0        0  0.0
445          0      180             78             63       14  59.4
673          3      123            100             35      240  57.3
691          8      187             76             30        0  0.0
704          10     115              0              0        0  0.0

     DiabetesPedigreeFunction  Age  Outcome  bmi_outlier
9                       0.232   54        1            0
49                      0.305   24        0            0
60                      0.304   21        0            0
81                      0.102   22        0            0
145                     0.082   21        0            0
177                     0.314   43        1            0
303                     0.279   21        0            0
332                     1.147   24        1            0
371                     0.279   21        0            0
426                     0.256   25        0            0
445                     2.420   25        1            0
673                     0.880   22        0            0
691                     0.904   26        0            0
704                     0.261   30        1            0
```

13. Correlation Heatmap

```
plt.figure(figsize=(11,7))
sns.heatmap(diabetes_data.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```

14. Pie Chart - Diabetes Outcome

```
diabetes_data['Outcome'].value_counts().plot.pie(autopct='%1.1f%%', startangle=90, colors=['lightcoral', 'lightgreen'])
plt.title('Diabetes Outcome Distribution')
plt.ylabel('')
plt.show()
```


15. Missing Value Imputation (if Any)

```
diabetes_data.isnull().sum()
```

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

```
### Group by analysis
```

```
diabetes_data.groupby('Outcome')[['Glucose', 'BMI', 'Age']].mean()
```

Outcome	Glucose	BMI	Age
0	109.980000	30.304200	31.190000
1	141.257463	35.142537	37.067164

Conclusion & Key Insights

- The dataset contains health-related attributes like Glucose, BloodPressure, Insulin, BMI, Age, etc., for predicting the likelihood of diabetes.
- **Data Quality**
  - No missing values in terms of `NaN`, but several columns had biologically invalid zero values.
  - These zero values were treated as missing and imputed using the mean/median to ensure clean and realistic data.
- **Statistical Summary**
  - Mean Glucose level is significantly higher in diabetic patients.
  - BMI and Age also show a higher average in people with diabetes.
- **Visual Insights**
  - Boxplots revealed several outliers in `Insulin`, `BMI`, and `SkinThickness`.
  - Distribution plots showed that features like `Glucose` and `BMI` are slightly right-skewed.
  - Countplots and pie charts revealed.
  - Around **35% of the people are diabetic (Outcome = 1)**.
  - Pregnancies and Age show clear differences between diabetic and non-diabetic groups.
- **Correlation Analysis**
  - `Glucose` and `BMI` show a positive correlation with the outcome.
  - `Pregnancies` and `Age` are also moderately correlated with the outcome.
- **Final Note**
  - The dataset is now clean and well-understood.
  - It is ready for further **feature engineering** and **machine learning modeling** to build a diabetes prediction system.