Diabetes Health Indicators Analysis

- This project analyzes the Diabetes Health Indicators Dataset (BRFSS 2015) to understand how lifestyle, health conditions, and demographic factors relate to diabetes prevalence.
- The main objective was to identify patterns and risk factors associated with diabetes using exploratory data analysis, statistical summaries, and visualization techniques.

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

We import required Python libraries for data analysis:

- pandas → data loading and manipulation
- numpy → numerical operations
- matplotlib → basic plotting
- seaborn → advanced statistical visualization
- These libraries form the core toolkit for exploratory data analysis.

```
df = pd.read_csv("diabetes_binary_health_indicators_BRFSS2015.csv")
df.head()
```

	Diabetes_binary	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDiseaseorAttack	PhysActivity	Fruits	..
0	0.0	1.0	1.0	1.0	40.0	1.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	25.0	1.0	0.0	0.0	1.0	0.0	
2	0.0	1.0	1.0	1.0	28.0	0.0	0.0	0.0	0.0	1.0	
3	0.0	1.0	0.0	1.0	27.0	0.0	0.0	0.0	1.0	1.0	
4	0.0	1.0	1.0	1.0	24.0	0.0	0.0	0.0	1.0	1.0	

5 rows × 22 columns

The dataset is loaded using pandas.

- read_csv(): Reads the CSV file into a DataFrame.
- head(): Displays the first five rows to understand dataset structure and columns.

```
df.shape # (rows, columns)
```

```
(253680, 22)
```

```
df.columns
```

```
Index(['Diabetes_binary', 'HighBP', 'HighChol', 'CholCheck', 'BMI', 'Smoker',
       'Stroke', 'HeartDiseaseorAttack', 'PhysActivity', 'Fruits', 'Veggies',
       'HvyAlcoholConsump', 'AnyHealthcare', 'NoDocbcCost', 'GenHlth',
       'MentHlth', 'PhysHlth', 'DiffWalk', 'Sex', 'Age', 'Education',
       'Income'],
      dtype='object')
```

Displays all feature names available in the dataset.

- Helps identify:

- health indicators
- lifestyle variables
- target variable (Diabetes)

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 253680 entries, 0 to 253679
Data columns (total 22 columns):
```

```
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   Diabetes_binary       253680 non-null  float64
 1   HighBP                253680 non-null  float64
 2   HighChol              253680 non-null  float64
 3   CholCheck             253680 non-null  float64
 4   BMI                   253680 non-null  float64
 5   Smoker                253680 non-null  float64
 6   Stroke                253680 non-null  float64
 7   HeartDiseaseorAttack  253680 non-null  float64
 8   PhysActivity          253680 non-null  float64
 9   Fruits                253680 non-null  float64
 10  Veggies               253680 non-null  float64
 11  HvyAlcoholConsump     253680 non-null  float64
 12  AnyHealthcare         253680 non-null  float64
 13  NoDocbcCost           253680 non-null  float64
 14  GenHlth               253680 non-null  float64
 15  MentHlth              253680 non-null  float64
 16  PhysHlth              253680 non-null  float64
 17  DiffWalk              253680 non-null  float64
 18  Sex                   253680 non-null  float64
 19  Age                   253680 non-null  float64
 20  Education             253680 non-null  float64
 21  Income                253680 non-null  float64
dtypes: float64(22)
memory usage: 42.6 MB
```

Provides:

- data types
- non-null counts
- memory usage
- Used to check if cleaning is required.

```
df.describe()
```

	Diabetes_binary	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDisea
count	253680.000000	253680.000000	253680.000000	253680.000000	253680.000000	253680.000000	253680.000000	25
mean	0.139333	0.429001	0.424121	0.962670	28.382364	0.443169	0.040571	
std	0.346294	0.494934	0.494210	0.189571	6.608694	0.496761	0.197294	
min	0.000000	0.000000	0.000000	0.000000	12.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	1.000000	24.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	1.000000	27.000000	0.000000	0.000000	
75%	0.000000	1.000000	1.000000	1.000000	31.000000	1.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	98.000000	1.000000	1.000000	

8 rows × 22 columns

Generates descriptive statistics:

- mean
- minimum
- maximum
- standard deviation
- Helps understand overall data distribution.

```
df.isnull().sum()
```

	0
Diabetes_binary	0
HighBP	0
HighChol	0
CholCheck	0
BMI	0
Smoker	0
Stroke	0
HeartDiseaseorAttack	0
PhysActivity	0
Fruits	0
Veggies	0
HvyAlcoholConsump	0
AnyHealthcare	0
NoDocbcCost	0
GenHlth	0
MentHlth	0
PhysHlth	0
DiffWalk	0
Sex	0
Age	0
Education	0
Income	0

dtype: int64

- Counts missing values in each column.
- Important because missing data can bias analysis.
- Result showed **no missing values**.

```
df.duplicated().sum()
```

```
np.int64(24206)
```

- Identifies repeated records.
- Duplicates can distort statistical results.

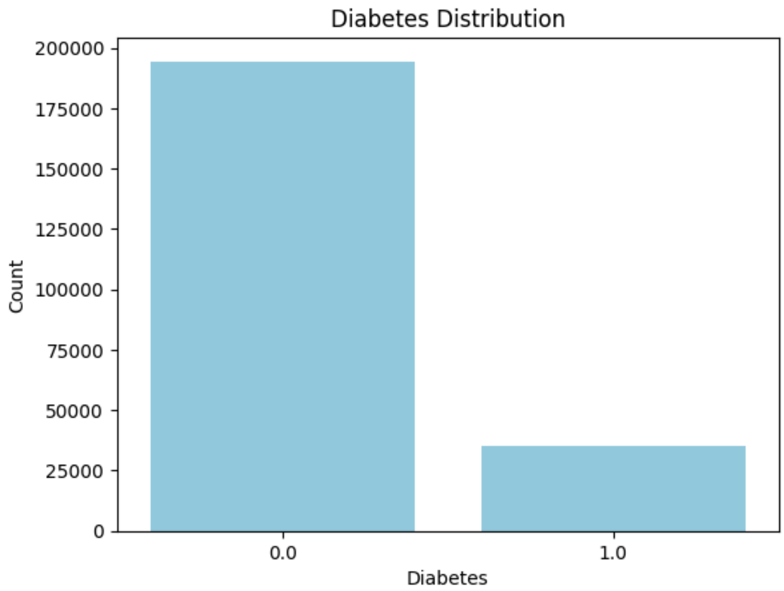
```
df = df.drop_duplicates() # Removes duplicate observations to ensure reliable analysis.
```

```
df.rename(columns={"Diabetes_binary": "Diabetes"}, inplace=True)
```

- Renames column for better readability.
- Cleaner naming improves analysis clarity.

Diabetes Distribution

```
sns.countplot(x="Diabetes", data=df, color="skyblue")
plt.xlabel("Diabetes")
plt.ylabel("Count")
plt.title("Diabetes Distribution")
plt.show()
```



Visualizes number of diabetic vs non-diabetic individuals.

- Used to check class imbalance.

Observation:

- Most individuals do not have diabetes.

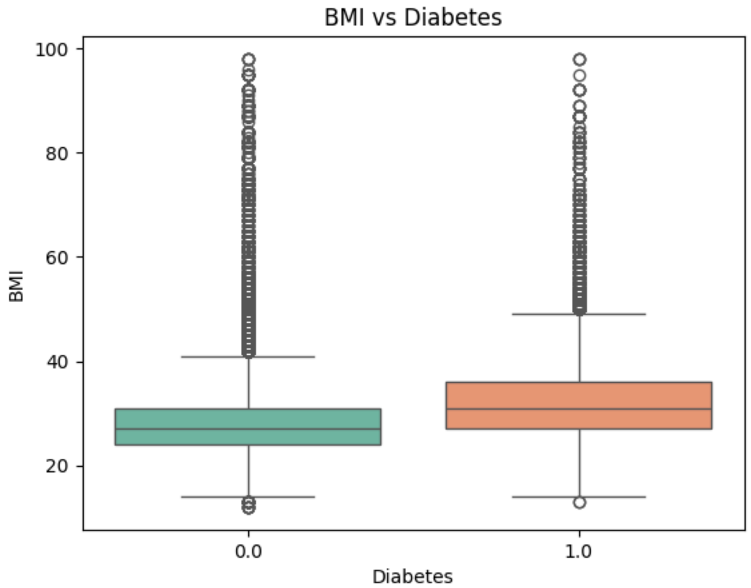
BMI vs Diabetes

```
sns.boxplot(x="Diabetes", y="BMI", data=df, palette='Set2')
plt.title("BMI vs Diabetes")
plt.show()
```

```
/tmp/ipython-input-3418311448.py:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable t

  sns.boxplot(x="Diabetes", y="BMI", data=df, palette='Set2')
```



Compares BMI distribution between groups.

Boxplot shows:

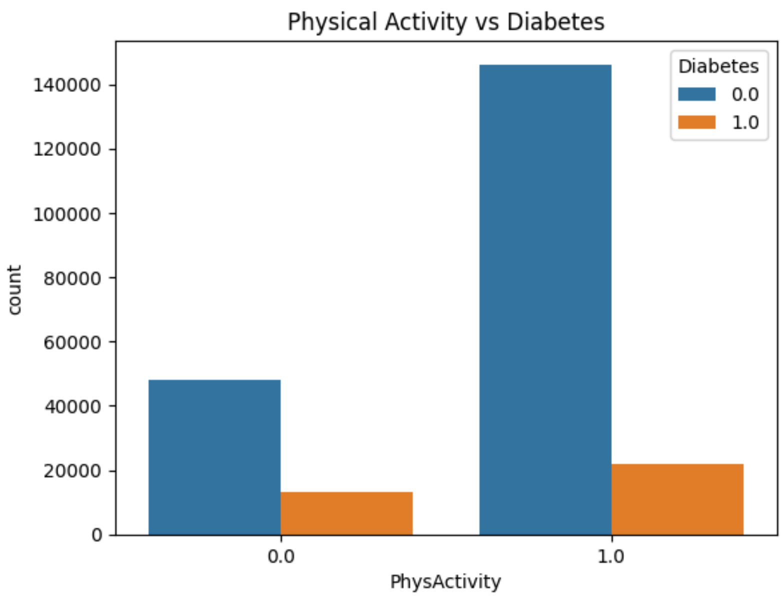
- median
- spread
- outliers

Insight:

- Diabetic individuals tend to have higher BMI.

Physical Activity Analysis

```
sns.countplot(x="PhysActivity", hue="Diabetes", data=df)
plt.title("Physical Activity vs Diabetes")
plt.show()
```



Explanation:

- Compares diabetes occurrence between active and inactive individuals.

Insight:

- Physically active individuals show lower diabetes prevalence.

GroupBy Analysis with Age

```
df.groupby("Age")["Diabetes"].mean() # Groups people by age category and calculates diabetes rate. Diabetes incr
```

Age	Diabetes
1.0	0.014154
2.0	0.019819
3.0	0.031328
4.0	0.051108
5.0	0.074715
6.0	0.100752
7.0	0.132866
8.0	0.155507
9.0	0.191421
10.0	0.222837
11.0	0.231437
12.0	0.219975
13.0	0.190578

dtype: float64

GroupBy with Lifestyle Factors

```
df.groupby("PhysActivity")["Diabetes"].mean()
```

PhysActivity	Diabetes
0.0	0.212831
1.0	0.131137

dtype: float64

Explanation

GroupBy operations helped summarize health patterns:

- Older individuals have higher diabetes rates.
- Smokers show slightly increased diabetes prevalence.
- Physically active individuals demonstrate lower diabetes occurrence.
- Poor general health correlates with higher diabetes likelihood.
- Compares diabetes rate between active and inactive groups.
- Used to evaluate lifestyle impact.

Pivot Table Analysis

```
pd.pivot_table(
    df,
    values="Diabetes",
    index="Age",
    columns="PhysActivity",
    aggfunc="mean"
)
```

PhysActivity	0.0	1.0
Age		
1.0	0.020053	0.013227
2.0	0.033079	0.017162
3.0	0.045054	0.028052
4.0	0.066349	0.046732
5.0	0.101735	0.066274
6.0	0.140618	0.087125
7.0	0.183114	0.113993
8.0	0.208432	0.134919
9.0	0.249245	0.169058
10.0	0.299747	0.194168
11.0	0.305101	0.202297
12.0	0.278545	0.193545
13.0	0.232285	0.168651

Explanation

Key findings:

- Older age groups combined with poor health status exhibit the highest diabetes prevalence.
- Physical activity reduces diabetes risk across nearly all age categories. -Health condition and lifestyle together influence diabetes more than a single factor.

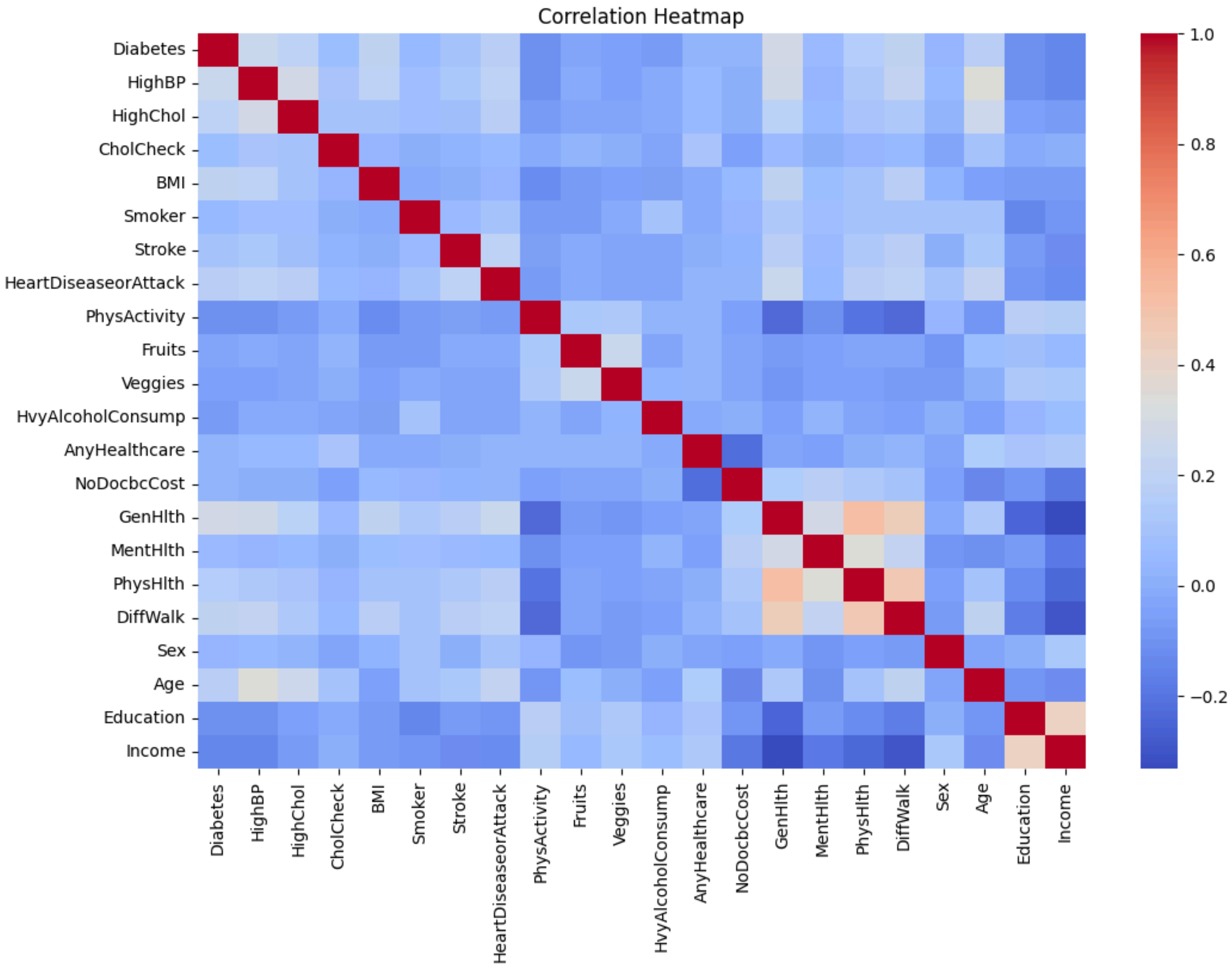
Creates a two-dimensional summary:

- Rows: Age groups (age code: 1.0-13.0)
- Columns: Physical activity

- Values: Diabetes rate
- Pivot tables allow multi-variable comparison simultaneously.

Correlation Heatmap

```
plt.figure(figsize=(12,8))
sns.heatmap(df.corr(), cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```



Diabetes is influenced by a combination of lifestyle and medical conditions rather than a single factor.

- -1: negative relation (Blue Color))
- 0: no relation (White Color)
- +1: strong relation (Darker Red color = stronger relationship.)
- The correlation heatmap was used to identify relationships between health indicators and diabetes occurrence.

Key observations include:

- BMI shows a positive correlation with diabetes, indicating higher body weight is associated with increased diabetes prevalence.
- Age demonstrates a positive relationship with diabetes, suggesting risk increases among older individuals.
- High blood pressure and heart disease indicators also show notable correlations with diabetes.
- Lifestyle factors such as physical activity display weaker or negative relationships, suggesting potential protective effects.
- Overall, diabetes appears influenced by multiple interconnected health conditions rather than a single factor.

Key Healthcare Insights:

From the analysis:

- Higher BMI significantly increases diabetes risk.
- Aging populations require stronger preventive healthcare strategies.
- Physical activity acts as a protective factor.
- Poor overall health strongly correlates with diabetes occurrence.
- Preventive lifestyle interventions may reduce diabetes prevalence.

Final Conclusion

This analysis demonstrates that diabetes is a multifactorial health condition influenced by age, lifestyle habits, and overall health status.

The findings highlight the importance of:

- Maintaining healthy body weight
- Encouraging regular physical activity
- Monitoring cardiovascular health
- Implementing early preventive healthcare programs
- Data-driven insights such as these can assist healthcare professionals and policymakers in developing effective diabetes prevention strategies