

DIABETES DIAGNOSIS ANALYSIS

19TH JUNE,2023

1 Problem Statement : Diabetes Diagnosis Analysis

1.1 Description:

Diabetes Mellitus is one of the currently deadliest diseases as it set the foundation for several conditions to develop in the body. Diabetes paves way for conditions such as high blood pressure, hyperlipidaemia, neuropathy, eye problems, kidney failure, among others. All these conditions also lead to other conditions that are also very dangerous to the body, making diabetes worth studied into more details. Between 2000 and 2019, there was a 3% increase in diabetes mortality rates by age. In 2019, diabetes and kidney disease due to diabetes caused an estimated 2 million deaths. In the diagnosis of diabetes, an important biomarker is blood glucose level, other biomarkers and physical characteristics play important role in the diagnosis as well. This article seeks the investigate the various factors involved in diabetes diagnosis to reveal new other more important features that can be used to detect the presence of diabetes and also to develop a Machine Learning Model to determine the diabetic state of a patient when their information is inputed.

2 1. Importing Libraries

```
In [1]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import
from sklearn.preprocessing import
from sklearn.ensemble import RandomForest
from sklearn.metrics import mean_squared_error
import warnings
warnings.filterwarnings('ignore')
```

2 The DataSets

2.1 DataSets Information

Column attribute Description Patient number Identifies patients by number Cholesterol Total cholesterol Glucose Fasting blood sugar HDL HDL or good cholesterol Chol/HDL Ratio of total cholesterol to good cholesterol. Desirable result is < 5 Age All adult African Americans

Gender 162 males, 228 females Height In inches Weight In pounds (lbs) BMI $703 \times \text{weight (lbs)} / [\text{height(inches)}]^2$ Systolic BP The upper number of blood pressure Diastolic BP The lower number of blood pressure Waist Measured in inches Hip Measured in inches Waist/hip Ratio is possibly a stronger risk factor for heart disease than BMI Diabetes Yes (60), No (330)

This dataset is a modified data from VanderBilt but the original dataset is from a study of rural African American in Virginia. The dataset already has 13 patients dropped due to missing data. It also has two features added, being Chol/HDL and Waist/hip.

2.2 Reading Datasets

```
In [2]: df = pd.read_csv('\\\\Users\\Daniel Appiah\\Desktop\\Diabetes_Classification.csv')
```

```
Out[2]:
```

	Cholesterol	Glucose	HDL Chol	Chol/HDL ratio	Age	Gender	Height	Weight	BMI	Systolic BP	Diastolic BP
Patient number											
1	193	77	49	3.9	19	female	61	119	22.5	118	78
2	146	79	41	3.6	19	female	60	135	26.4	108	85
3	217	75	54	4.0	20	female	67	187	29.3	110	77
4	226	97	70	3.2	20	female	64	114	19.6	122	68
5	164	91	67	2.4	20	female	70	141	20.2	122	88

2.3 Data Exploration

```
In [3]: df.head()
```

```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 390 entries, 1 to 390
Data columns (total 17 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Cholesterol            390 non-null    int64
1   Glucose                390 non-null    int64
2   HDL Chol              390 non-null    int64
3   Chol/HDL ratio        390 non-null    float64
4   Age                   390 non-null    int64
5   Gender                390 non-null    object
6   Height                390 non-null    int64
7   Weight                390 non-null    int64
8   BMI                   390 non-null    float64
9   Systolic BP           390 non-null    int64
10  Diastolic BP           390 non-null    int64
11  waist                 390 non-null    int64
12  hip                   390 non-null    int64
13  Waist/hip ratio        390 non-null    float64
14  Diabetes               390 non-null    object
15  Unnamed: 16            1 non-null      float64
16  Unnamed: 17            1 non-null      float64
dtypes: float64(5), int64(10), object(2)
memory usage: 54.8+ KB

```

All features here are numeric except the column named Diabetes.

In [4]:

```

.      ()

```

Out[4]:

	Cholesterol	Glucose	HDL Chol	Chol/HDL ratio	Age	Height	Weight	
count	390.000000	390.000000	390.000000	390.000000	390.000000	390.000000	390.000000	390
mean	207.230769	107.338462	50.266667	4.524615	46.774359	65.951282	177.407692	28
std	44.666005	53.798188	17.279069	1.736634	16.435911	3.918867	40.407824	6
min	78.000000	48.000000	12.000000	1.500000	19.000000	52.000000	99.000000	15
25%	179.000000	81.000000	38.000000	3.200000	34.000000	63.000000	150.250000	24
50%	203.000000	90.000000	46.000000	4.200000	44.500000	66.000000	173.000000	27
75%	229.000000	107.750000	59.000000	5.400000	60.000000	69.000000	200.000000	32
max	443.000000	385.000000	120.000000	19.300000	92.000000	76.000000	325.000000	55

In [5]:

```

.      ()

```

Out[5]:

	Cholesterol	Glucose	HDL Chol	Chol/HDL ratio	Age	Height	Weight	BMI
Cholesterol	1.000000	0.158102	0.193162	0.475927	0.247333	-0.063601	0.062359	0.091695
Glucose	0.158102	1.000000	-0.158302	0.282210	0.294392	0.098052	0.190358	0.129286
HDL Chol	0.193162	-0.158302	1.000000	-0.681867	0.028210	-0.087238	-0.291883	-0.241860
Chol/HDL ratio	0.475927	0.282210	-0.681867	1.000000	0.163201	0.081162	0.278812	0.228407
Age	0.247333	0.294392	0.028210	0.163201	1.000000	-0.082229	-0.056784	-0.009164
Height	-0.063601	0.098052	-0.087238	0.081162	-0.082229	1.000000	0.255389	-0.259589
Weight	0.062359	0.190358	-0.291883	0.278812	-0.056784	0.255389	1.000000	0.860147
BMI	0.091695	0.129286	-0.241860	0.228407	-0.009164	-0.259589	0.860147	1.000000
Systolic BP	0.207741	0.162777	0.031807	0.115505	0.453417	-0.040704	0.097497	0.121408
Diastolic BP	0.166241	0.020262	0.078342	0.038242	0.068649	0.043617	0.166477	0.145304
waist	0.134038	0.222336	-0.276697	0.313262	0.150585	0.057447	0.847766	0.810707
hip	0.093364	0.138223	-0.223837	0.208902	0.004675	-0.095906	0.826985	0.881728
Waist/hip ratio	0.091847	0.185117	-0.158777	0.243329	0.275188	0.252548	0.250461	0.100873
Unnamed: 16	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Unnamed: 17	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

2.4 Handling Missing Data

In [6]:

```
.dropna(inplace=True)
```

Out[6]:

```
Cholesterol      0
Glucose          0
HDL Chol         0
Chol/HDL ratio   0
Age              0
Gender           0
Height           0
Weight           0
BMI              0
Systolic BP      0
Diastolic BP     0
waist            0
hip              0
Waist/hip ratio  0
Diabetes         0
Unnamed: 16      389
Unnamed: 17      389
dtype: int64
```

The data has no missing values except for the last 2 unnamed features, which will be dropped due to the large number of null values.

```
In [7]: = . ([ 'Unnamed: 16', 'Unnamed: 17'], =1)
```

```
Out[7]: Index(['Cholesterol', 'Glucose', 'HDL Chol', 'Chol/HDL ratio', 'Age', 'Gender',  
             'Height', 'Weight', 'BMI', 'Systolic BP', 'Diastolic BP', 'waist',  
             'hip', 'Waist/hip ratio', 'Diabetes'],  
           dtype='object')
```

2.5 Categorical Features

```
In [8]: = . (lambda : . ())
```

```
Out[8]: Cholesterol      153  
        Glucose          116  
        HDL Chol         75  
        Chol/HDL ratio   69  
        Age              68  
        Gender           2  
        Height           22  
        Weight           139  
        BMI              193  
        Systolic BP      71  
        Diastolic BP     56  
        waist            30  
        hip              32  
        Waist/hip ratio   39  
        Diabetes         2  
        dtype: int64
```

From this and a critical look at the data, the 'Gender' and 'Diabetes' columns are nominal features and must be changed to categorical data type.

```
In [9]: ['Gender'] = ['Gender']. ('category')  
        ['Diabetes'] = ['Diabetes']. ('category')  
        ['Diabetes'].
```

```
Out[9]: CategoricalDtype(categories=['Diabetes', 'No diabetes'], ordered=False)
```

3. Data Visualization

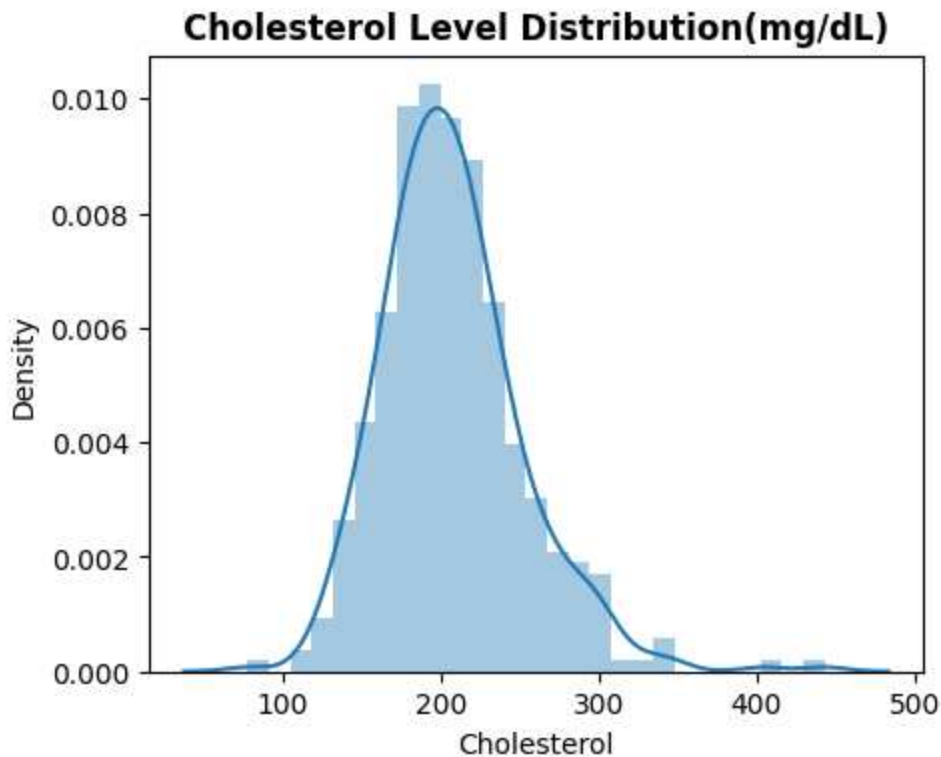
3.1 Visualising the distribution of the data

Cholesterol level

```
In [10]:
#Plotting the distribution of cholesterol level
fig,ax=plt.subplots(figsize=(5,4))
ax.hist(cholesterol)
ax.set_title('Cholesterol Level Distribution(mg/dL)', fontdict ={'fontweight': 'bold'})
#Classifying the cholesterol level.
Desirable=[cholesterol[cholesterol<200].shape[0]]
Borderline=[(cholesterol[cholesterol>=200]&(cholesterol<240)).shape[0]]
High=[cholesterol[cholesterol>=240].shape[0]]

print(f'Desirable Range (below 200 mg/dL): {Desirable} patients.')
print(f'Borderline High Range (200-239 mg/dL): {Borderline} patients.')
print(f'High Range (240 mg/dL and above): {High} patients.')
```

Desirable Range (below 200 mg/dL): 184 patients.
 Borderline High Range (200-239 mg/dL): 130 patients.
 High Range (240 mg/dL and above): 76 patients.

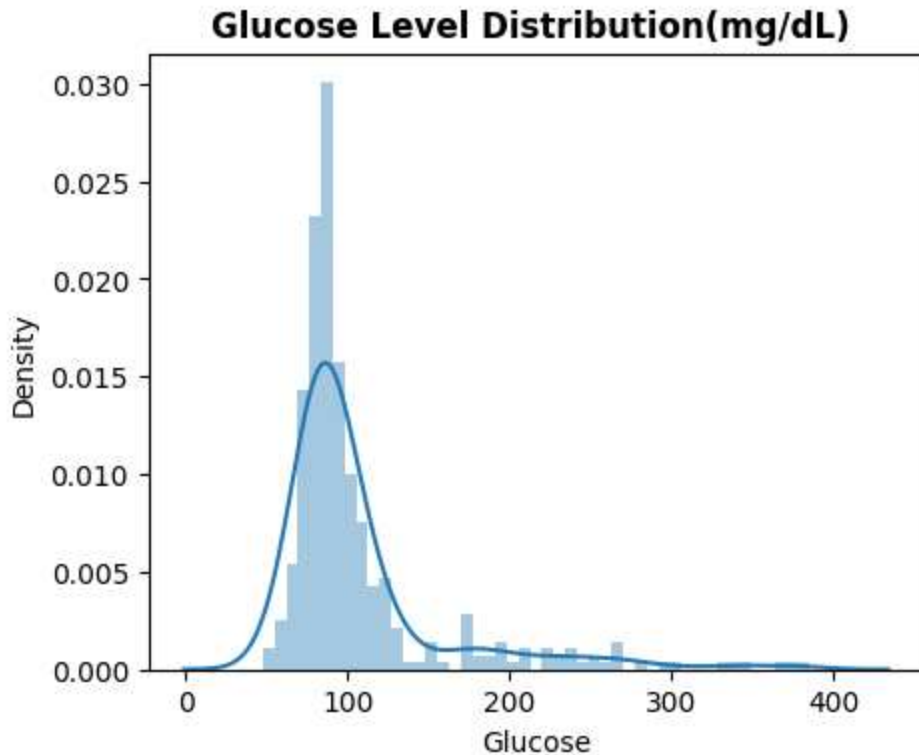


Glucose level

```
In [11]:
#Plotting the distribution of glucose level
fig,ax=plt.subplots(figsize=(5,4))
ax.hist(glucose)
ax.set_title('Glucose Level Distribution(mg/dL) ', fontdict ={'fontweight': 'bold'})
#Classifying the glucose level.
Normal=[glucose[glucose<100].shape[0]]
Prediabetes=[(glucose[glucose>=100]&(glucose<125)).shape[0]]
Diabetes=[glucose[glucose>=126].shape[0]]

print(f'Normal Range (below 100 mg/dL): {Normal} patients.')
print(f'Prediabetes Range (100-125 mg/dL): {Prediabetes} patients.')
print(f'Diabetes Range (126 mg/dL and above): {Diabetes} patients.')
```

Normal Range (below 100 mg/dL): 260 patients.
 Prediabetes Range (100-125 mg/dL): 69 patients.
 Diabetes Range (126 mg/dL and above): 60 patients.



High density Lipoprotein

In [12]:

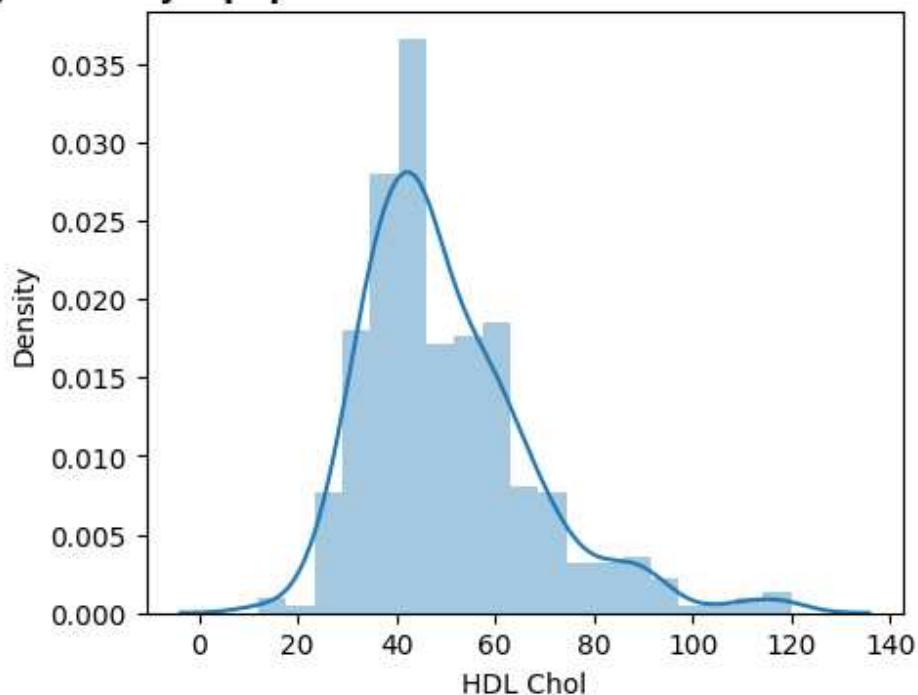
```
.      (      =(5,4))
.      ( ['HDL Chol'])
.      ('High Density Lipoprotein Cholesterol Level Distribution(mg/dL)',

      =      [( ['HDL Chol'] >= 40) & ( ['HDL Chol'] < 60)].      ()[
      =      [( ['HDL Chol'] >= 50) & ( ['HDL Chol'] < 60)].      ()
=      [ ['HDL Chol'] <40 ].      ()[0]
=      [ ['HDL Chol'] <50 ].      ()[0]
=      [ ['HDL Chol'] >= 60].      ()[0]

(f'Low Range for men (below 40 mg/dL): {      } patients.')
(f'Low Range for women (below 50 mg/dL): {      } patients.')
(f'Normal HDL Range for men (40-59 mg/dL): {      } patients.')
(f'Normal HDL Range for women(50-59 mg/dL): {      } patients.')
(f'High HDL Range(60 mg/dL and above): {      } patients.')
```

Low Range for men (below 40 mg/dL): 108 patients.
 Low Range for women (below 50 mg/dL): 226 patients.
 Normal HDL Range for men (40-59 mg/dL): 189 patients.
 Normal HDL Range for women(50-59 mg/dL): 71 patients.
 High HDL Range(60 mg/dL and above): 93 patients.

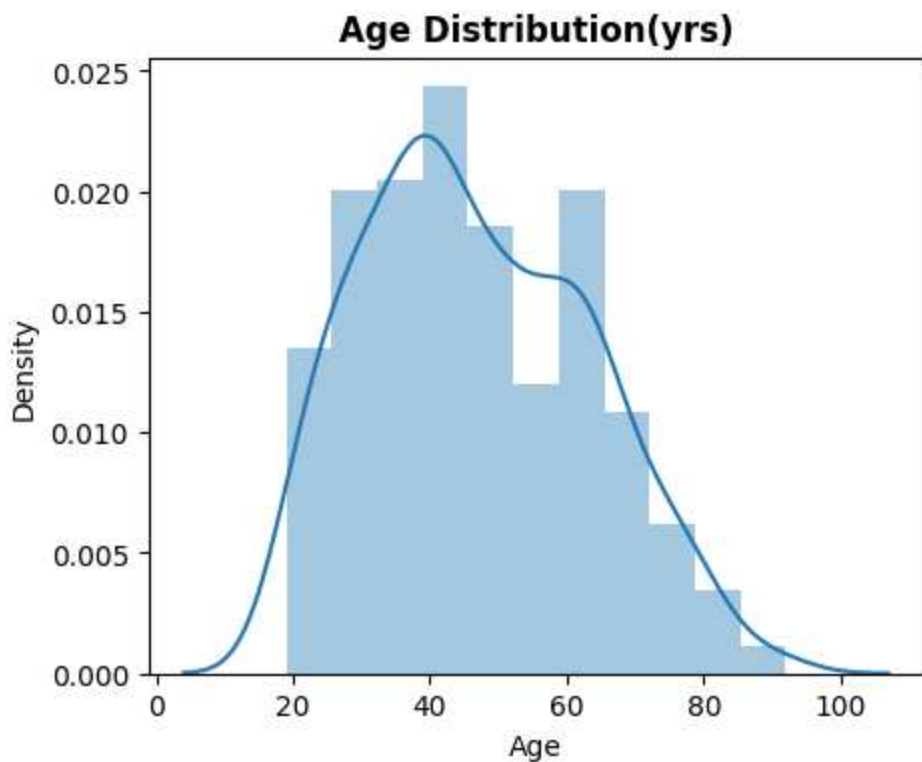
High Density Lipoprotein Cholesterol Level Distribution(mg/dL)



Age

```
In [13]: .      (      =(5,4))  
.      (      .      )  
.      ('Age Distribution(yrs)',      ,      ={'fontweight': 'bold'})
```

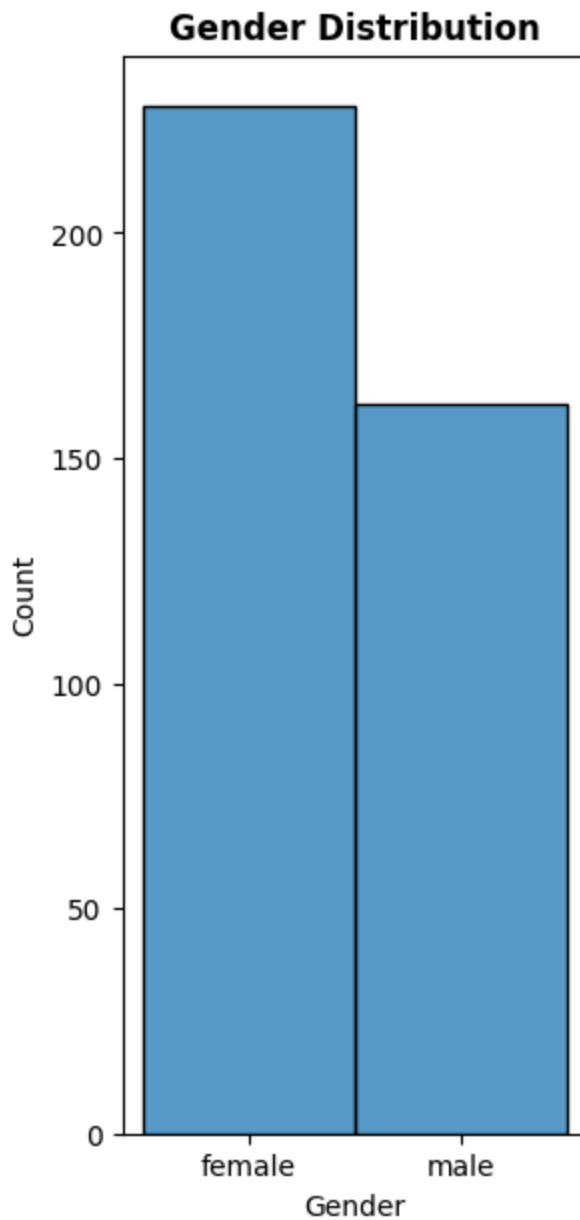
```
Out[13]: Text(0.5, 1.0, 'Age Distribution(yrs)')
```



Gender

```
In [14]: .plot(kind='bar', x='Gender', y='Count', title='Gender Distribution', color='blue', style='solid', figsize=(3,7))
         .set_xlabel('Gender')
         .set_ylabel('Count')
         .set_title('Gender Distribution', fontweight='bold')
```

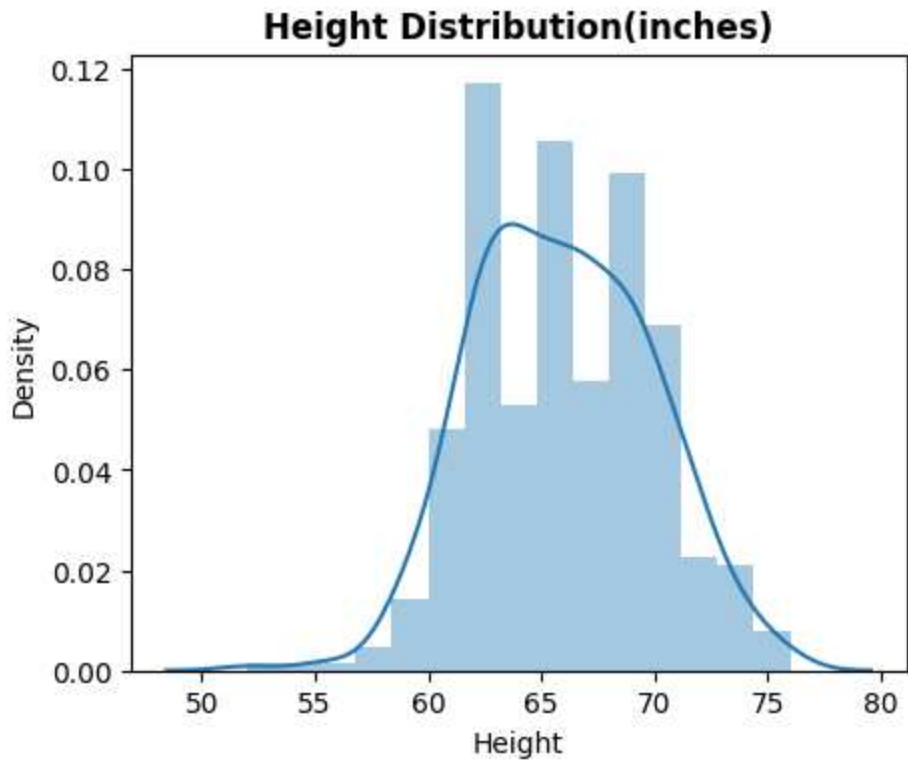
Out[14]: Text(0.5, 1.0, 'Gender Distribution')



Height

```
In [15]: .plot(kind='bar', x='Height (inches)', y='Count', title='Height Distribution(inches)', color='blue', style='solid', figsize=(5,4))
         .set_xlabel('Height (inches)')
         .set_ylabel('Count')
         .set_title('Height Distribution(inches)', fontweight='bold')
```

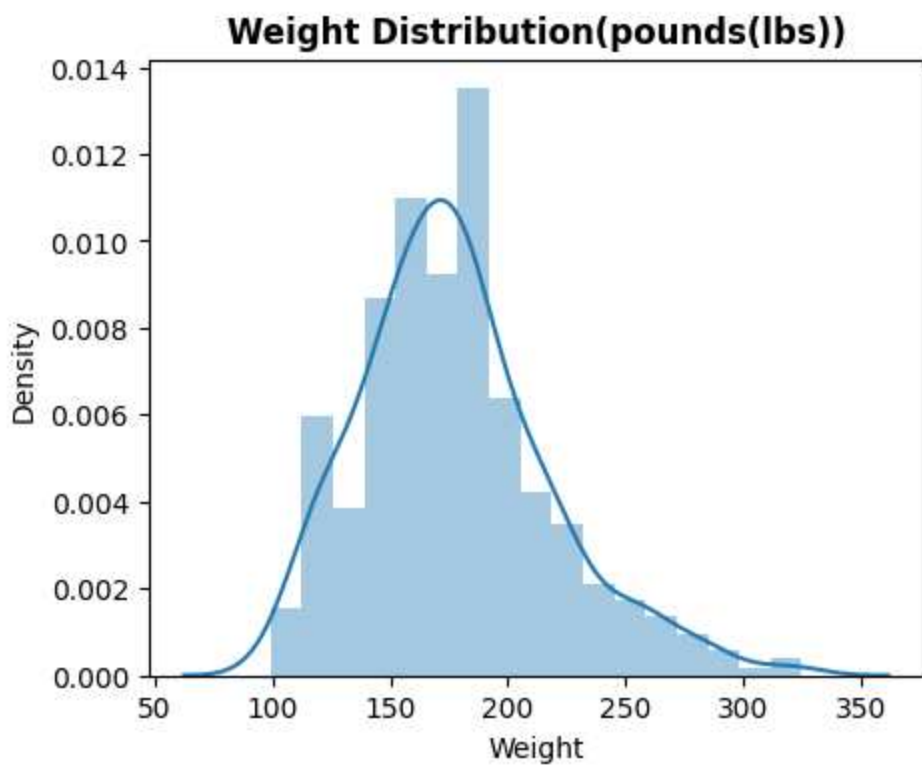
Out[15]: Text(0.5, 1.0, 'Height Distribution(inches)')



Weight

```
In [16]: .      (      =(5,4))
          .      (      )
          .      ('Weight Distribution(pounds(lbs))',      ={'fontweight': 'bold'})
```

```
Out[16]: Text(0.5, 1.0, 'Weight Distribution(pounds(lbs))')
```



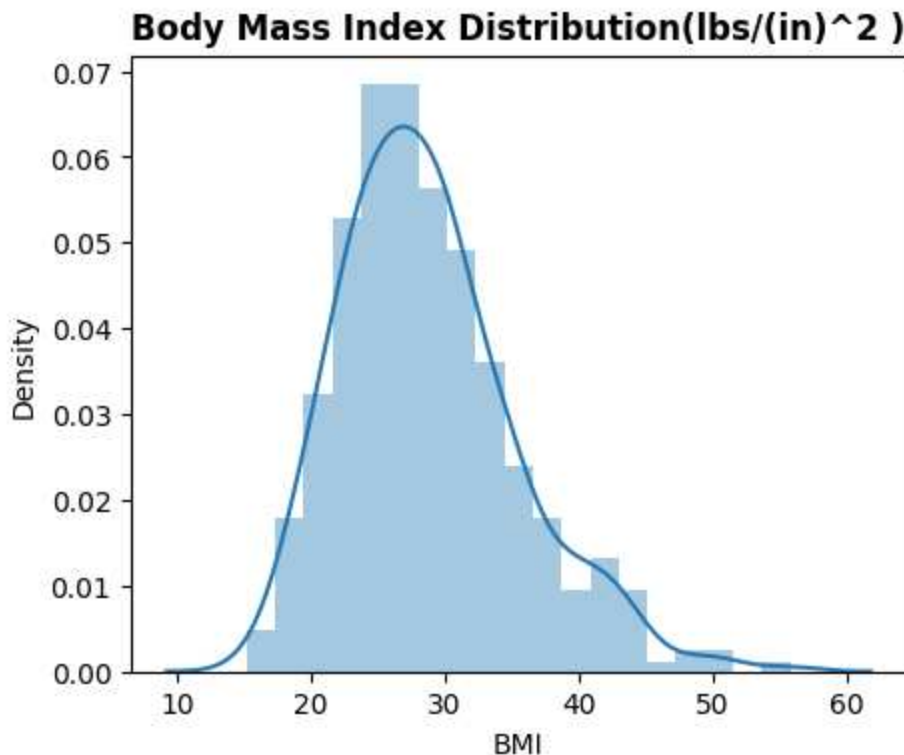
Body Mass Index

```
In [17]:
# Create a histogram of BMI values
fig, ax = plt.subplots(figsize=(5,4))
ax.hist(BMI, bins=10, density=True)
ax.set_title('Body Mass Index Distribution(lbs/(in)^2 )', fontweight='bold')

# Define BMI categories
underweight = BMI[BMI < 18.5].shape[0]
normal_weight = BMI[(BMI >= 18.5) & (BMI < 24.9)].shape[0]
overweight = BMI[(BMI >= 25.5) & (BMI < 30)].shape[0]
obese = BMI[BMI >= 30].shape[0]

# Print the number of patients in each category
print(f'Underweight (below 18.5 lbs/in^2): {underweight} patients.')
print(f'Normal weight (18.5-24.9 lbs/in^2): {normal_weight} patients.')
print(f'Overweight (25-29.9 lbs/in^2): {overweight} patients.')
print(f'Obese (30 lbs/in^2 and above): {obese} patients.')
```

Underweight (below 18.5 lbs/in²): 9 patients.
Normal weight (18.5-24.9 lbs/in²): 106 patients.
Overweight (25-29.9 lbs/in²): 107 patients.
Obese (30 lbs/in² and above): 150 patients.



The BMI classes are as follows: underweight (BMI less than 18.5), normal weight (BMI between 18.5 and 24.9), overweight (BMI between 25 and 29.9), obesity (Class I, BMI between 30 and 34.9), obesity (Class II, BMI between 35 and 39.9), and obesity (Class III, BMI 40 or higher)

Systolic Blood Pressure

```
In [18]:
# Create a histogram of Systolic Blood Pressure values
fig, ax = plt.subplots(figsize=(5,4))
ax.hist(SBP, bins=10, density=True)
```

```

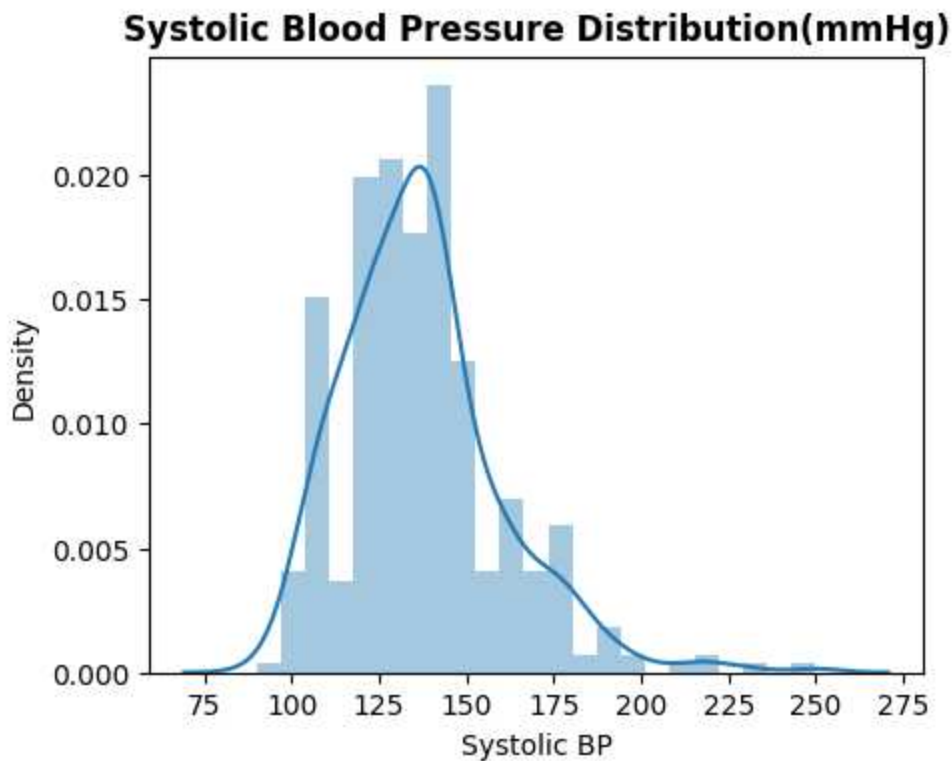
.      ('Systolic Blood Pressure Distribution(mmHg)',      ={'fontweight

```

```

Out[18]: Text(0.5, 1.0, 'Systolic Blood Pressure Distribution(mmHg)')

```



The systolic blood pressure (SBP) categories are as follows: normal (SBP below 120 mmHg but not up to 90mmHg), elevated (SBP between 120 and 129 mmHg), hypertension stage 1 (SBP between 130 and 139 mmHg), hypertension stage 2 (SBP 140 mmHg or higher), and hypertensive crisis (SBP higher than 180 mmHg and/or diastolic blood pressure (DBP) higher than 120 mmHg). This data has few portion below 120mmHg and the rest above.

Diastolic Blood Pressure

```

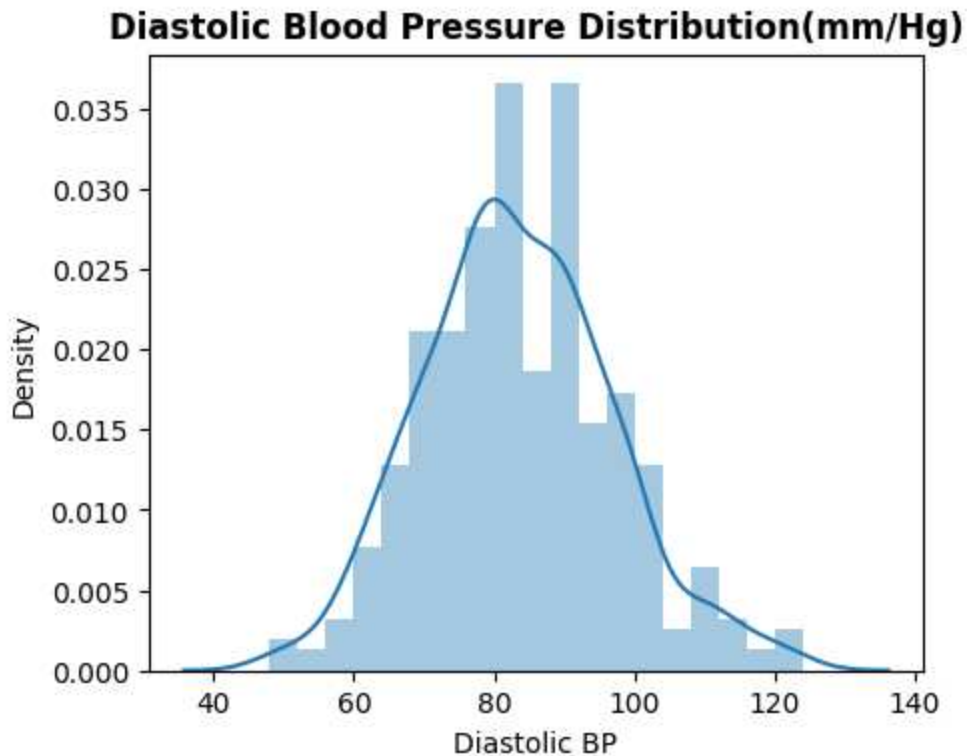
In [19]: .      (      =(5,4))
.      (      ['Diastolic BP'])
.      ('Diastolic Blood Pressure Distribution(mm/Hg)',      ={'fontweig

```

```

Out[19]: Text(0.5, 1.0, 'Diastolic Blood Pressure Distribution(mm/Hg)')

```

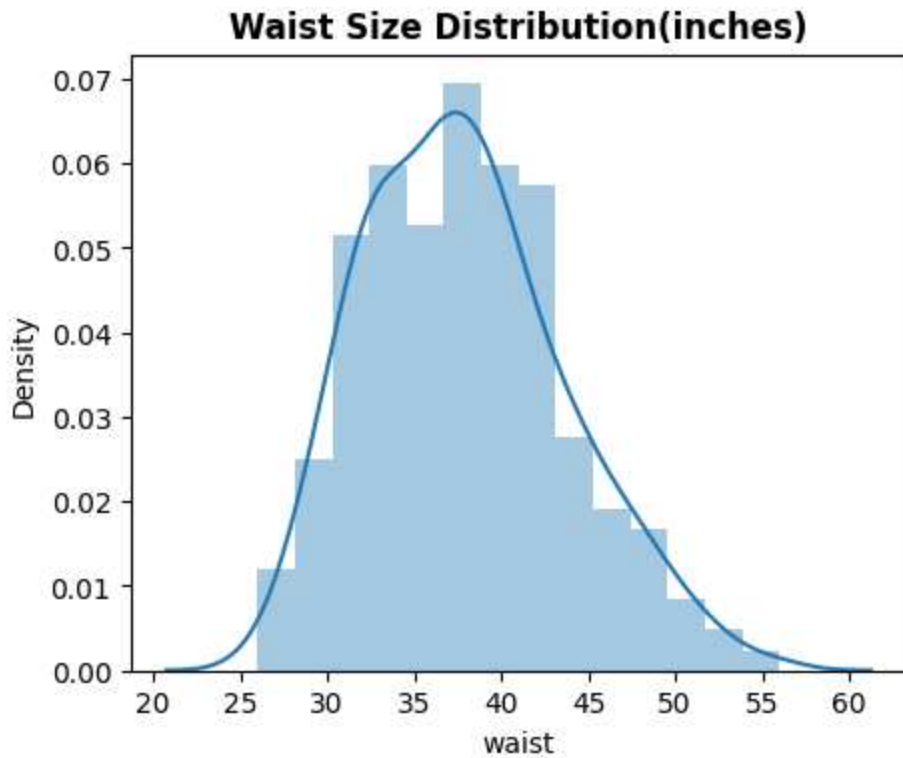


The diastolic blood pressure (DBP) categories are as follows: normal (DBP below 80 mmHg but not up to 60mmHg), elevated (DBP between 80 and 89 mmHg), hypertension stage 1 (DBP between 90 and 99 mmHg), hypertension stage 2 (DBP 100 mmHg or higher), and hypertensive crisis (DBP higher than 120 mmHg and/or systolic blood pressure (SBP) higher than 180 mmHg).

Waist size

```
In [20]: .      (      =(5,4))
          .      ( ['waist'])
          .      ('Waist Size Distribution(inches)',      ={'fontweight': 'bold'})
```

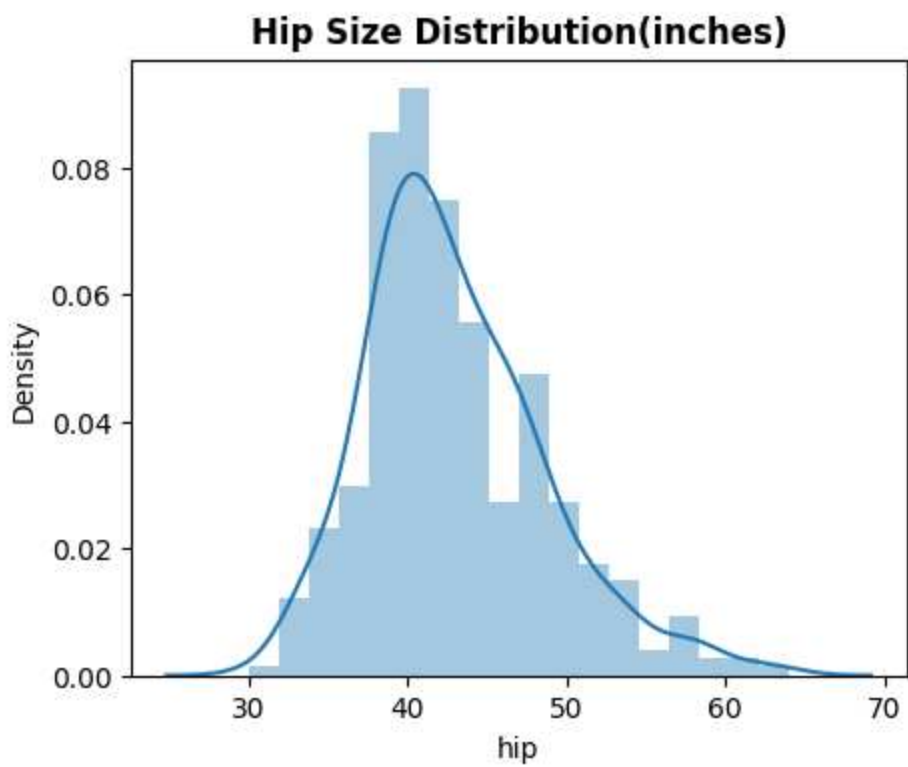
```
Out[20]: Text(0.5, 1.0, 'Waist Size Distribution(inches)')
```



Hip Size

```
In [21]: .      (      =(5,4))  
.      (      ['hip'])  
.      ('Hip Size Distribution(inches)',      ='fontweight': 'bold'))
```

```
Out[21]: Text(0.5, 1.0, 'Hip Size Distribution(inches)')
```



4 Correlation Analysis

4.1 Categorical Feature Analysis

```
In [22]: from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
['Diabetes'] = label_encoder.fit_transform(['Diabetes'])
['Gender'] = label_encoder.fit_transform(['Gender'])
label_map = {0: 1, 1: 0}
['Diabetes'] = ['Diabetes'].map(label_map)

# new ()
```

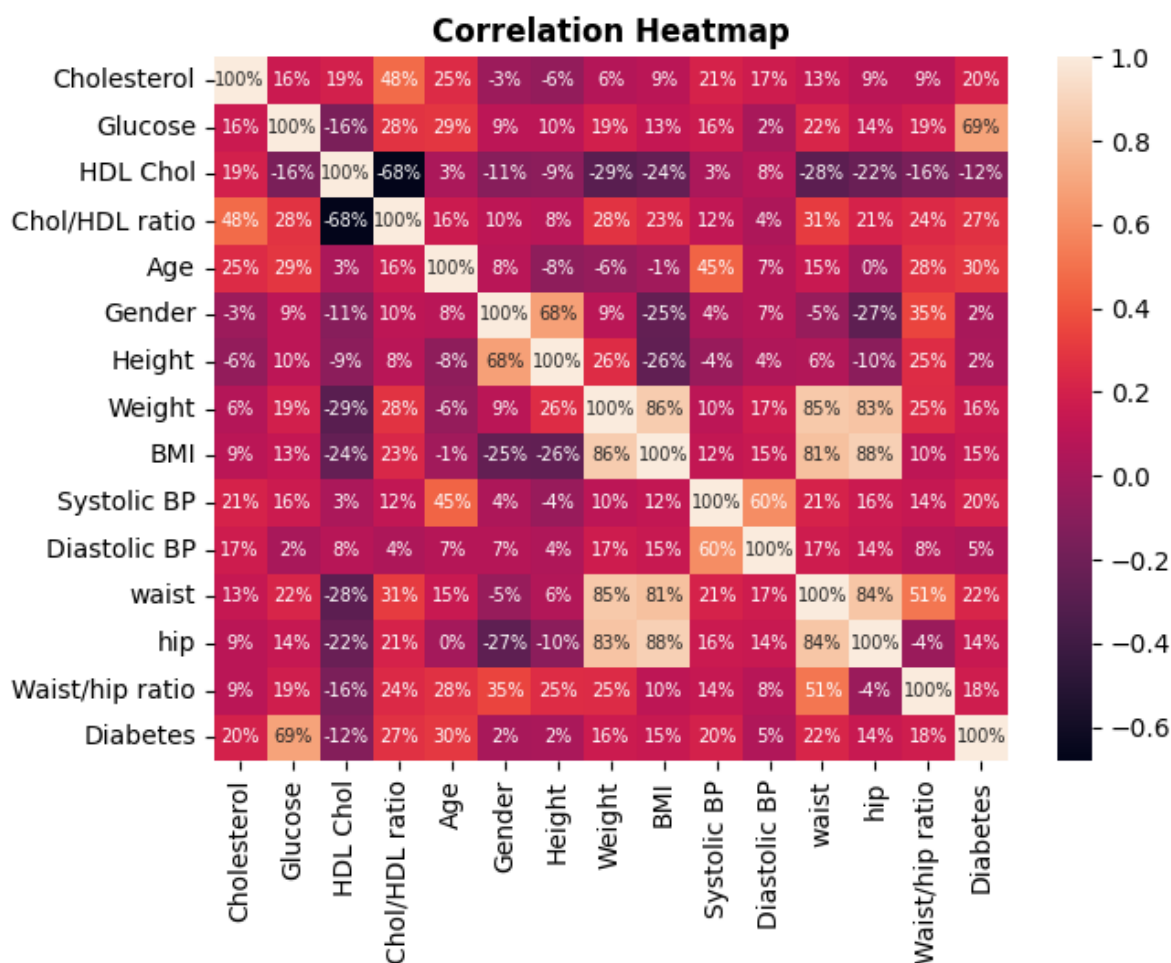
```
Out[22]:
```

	Cholesterol	Glucose	HDL Chol	Chol/HDL ratio	Age	Gender	Height	Weight	BMI	Systolic BP	Diastol E
Patient number											
1	193	77	49	3.9	19	0	61	119	22.5	118	7
2	146	79	41	3.6	19	0	60	135	26.4	108	5
3	217	75	54	4.0	20	0	67	187	29.3	110	7
4	226	97	70	3.2	20	0	64	114	19.6	122	6
5	164	91	67	2.4	20	0	70	141	20.2	122	8

4.2 Visualizing the correlation among the various features of the data

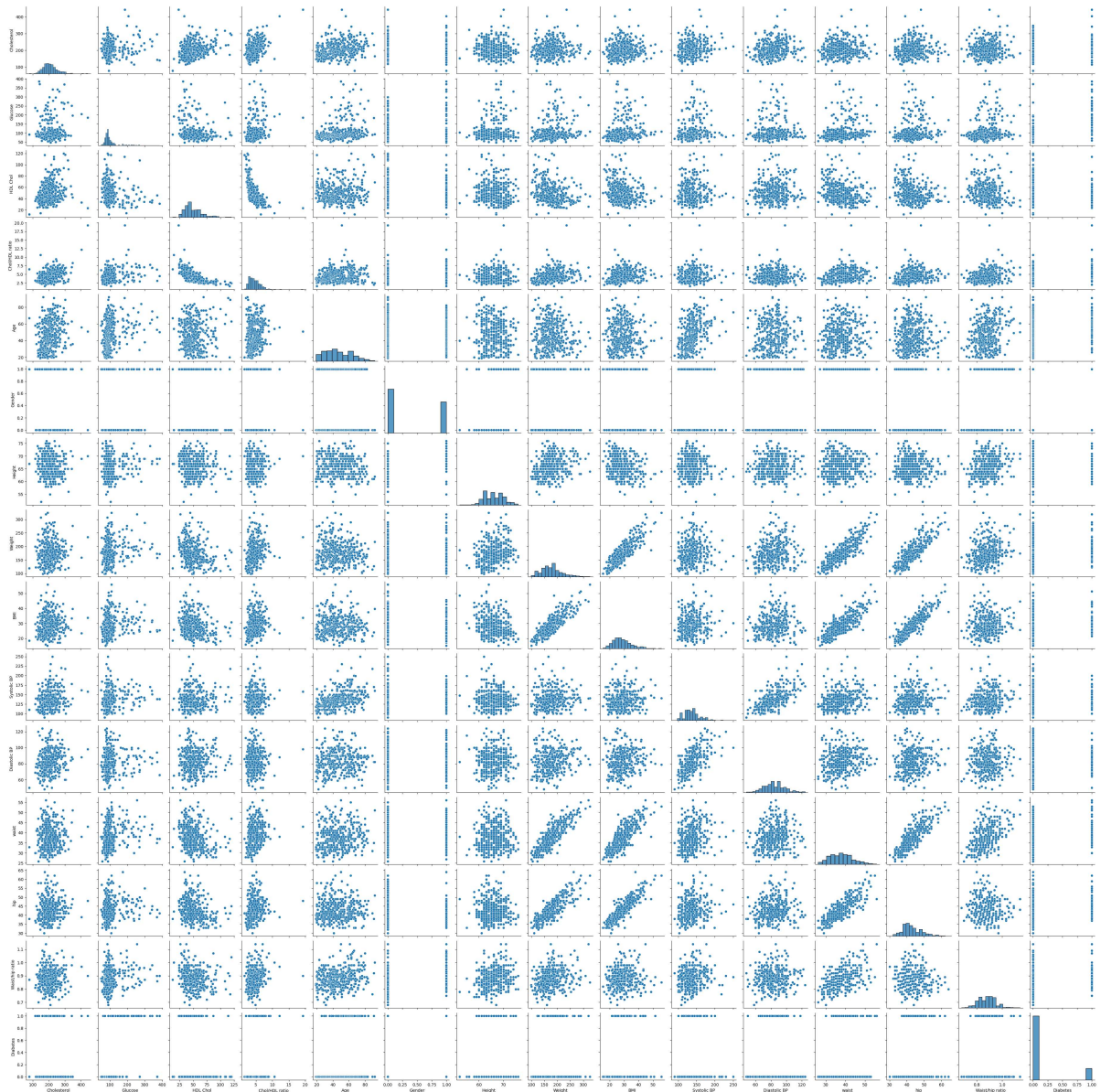
```
In [23]: plt.figure(figsize=(10, 8))
plt.title('Correlation Heatmap', fontweight='bold')
plt.imshow(corr, cmap=cm.RdBu, vmin=-.1, vmax=.1, cbar= True)
```

```
Out[23]: <AxesSubplot: title={'center': 'Correlation Heatmap'}>
```



```
In [24]: #cat= df['Diabetes_encoded', 'Gender_encoded']
#data= df.drop(cat)
        ( ) = (15,15)
        ( )
```

```
Out[24]: <seaborn.axisgrid.PairGrid at 0x282415ddd0>
<Figure size 1500x1500 with 0 Axes>
```

Let us take a look at features with very good correlation.

In [25]:

```

correlation = df.corr()
features = []
for i in range(len(correlation)):
    for j in range(i + 1, len(correlation)):
        if (correlation.loc[features[i], features[j]] > 0.30):
            features = (features + [features[i], features[j]]).tolist()
            continue
    features = (features + [features[i]]).tolist()

```

```

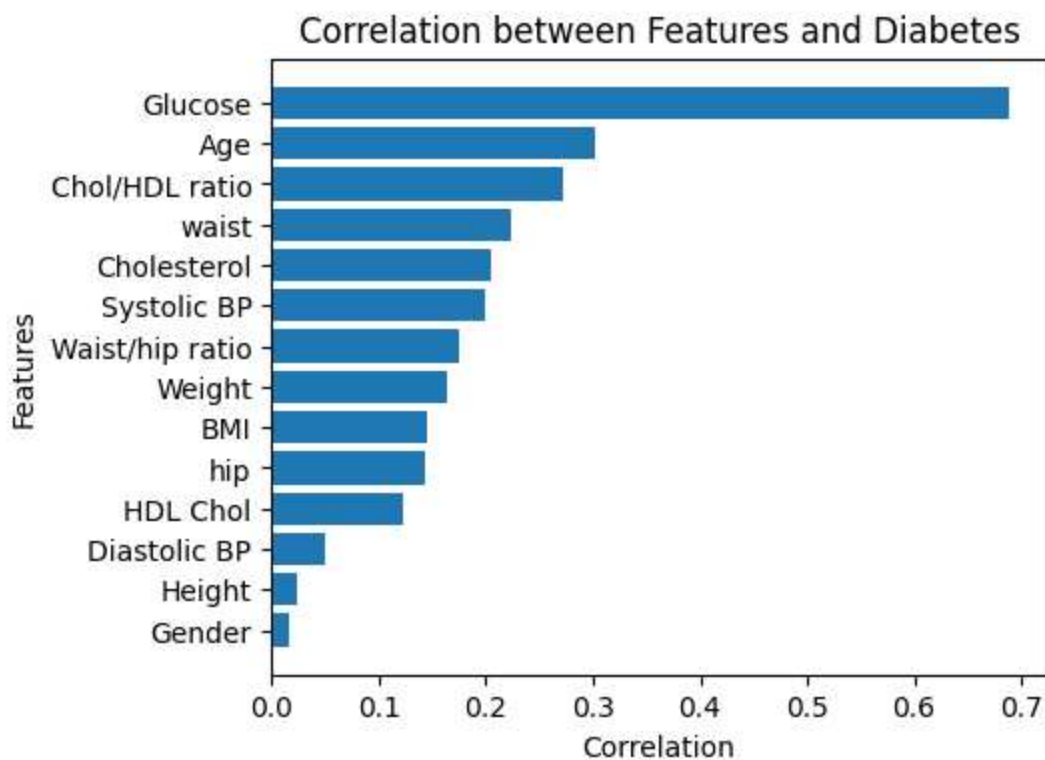
[('Cholesterol', 'Chol/HDL ratio'), ('Glucose', 'Diabetes'), ('HDL Chol', 'Chol/HDL ratio'), ('Chol/HDL ratio', 'waist'), ('Age', 'Systolic BP'), ('Age', 'Diabetes'), ('Gender', 'Height'), ('Gender', 'Waist/hip ratio'), ('Weight', 'BMI'), ('Weight', 'waist'), ('Weight', 'hip'), ('BMI', 'waist'), ('BMI', 'hip'), ('Systolic BP', 'Diastolic BP'), ('waist', 'hip'), ('waist', 'Waist/hip ratio')]

```

The pairs above show features that have correlation coefficient above plus or minus 0.3 .

4.3 Visualizing correlation between features and target(Diabetes column)

```
In [26]: correlation_matrix = r.corr()
target_correlation = correlation_matrix['Diabetes']
target_correlation = target_correlation.to_numpy().flatten()
target_correlation = target_correlation.reshape(1)
fig, ax = plt.subplots(figsize=(5, 4))
fig.set(target_correlation.index, target_correlation.values)
fig.set_ylabel('Correlation')
fig.set_xlabel('Features')
fig.set('Correlation between Features and Diabetes')
fig.show()
```



From the graph we can see that glucose level has the highest correlation coefficient with Diabetes, then surprisingly, age through to height having the lowest correlation coefficient with Diabetes.

4. 4 Exploring new features

Since the age seems to have a good correlation, let us utilise it in exploring new features with higher correlation.

```
In [27]: #creating square of the ages feature
         = (    )**2
         =    ()
         ['Age_square']=
```

Waist seems to have a good correlation with Diabetes, I am creating a new feature $((\text{waist})^2/\text{Age})$ to see how it will correlate with diabetes since a relationship between a person's waist and age can reveal obesity.

```
In [28]: square_waist_per_age = ['waist']**2 / ['Age']
         new_feature ['Square_Waist/Age']= square_waist_per_age
```

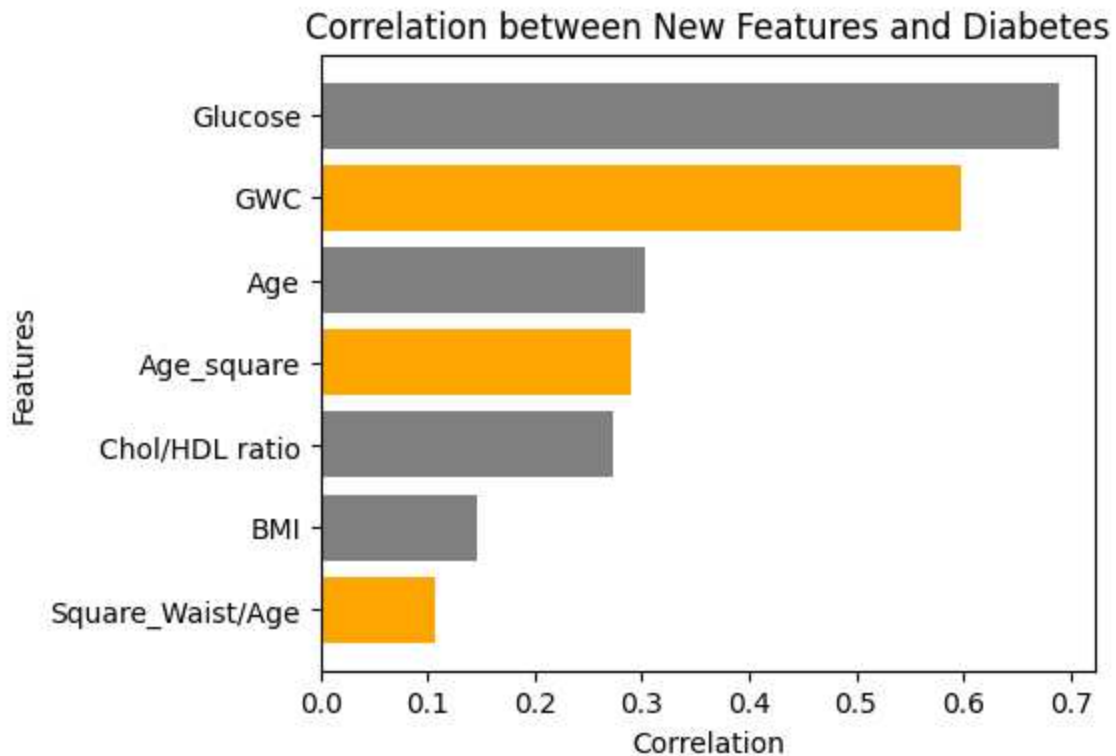
Creating another feature which is square root of (Glucose level * Weight * (Chol/HDL))

```
In [29]: = . ( . * . * ['Chol/HDL ratio'])
          ['GWC'] =
```

```
In [30]: new_features['Diabetes']= 1. Diabetes
new_features['Glucose']= 1. Glucose
new_features['BMI']= 1. BMI
new_features['Chol/HDL ratio']= ['Chol/HDL ratio']
new_features['Age']= 1. Age

corr_matrix = new_features.corr()
target_correlation = corr_matrix['Diabetes']
target_correlation = target_correlation.sort_values(ascending=False)
target_correlation = target_correlation.drop('Diabetes')
fig, ax = plt.subplots(5, 4)
cols = ['orange', 'grey', 'grey', 'orange', 'grey', 'orange', 'grey']
ax = ax.reshape(target_correlation.index, target_correlation.values, color = cols)
ax.set('Correlation')
ax.set('Features')
ax.set('Correlation between New Features and Diabetes')
ax.set('')

print(f'Correlation Coefficient of GWC is {target_correlation.GWC} whilst t
```



Correlation Coefficient of GWC is 0.5975911038445685 whilst that of glucose is 0.6890795038664445

From the graph, it could be revealed that the new feature GWC which is the square root of (Weight * Glucose Level * (cholesterol level/HDL level)) tends to be of a very high correlation coefficient with Diabetes and can be a very useful factor in diagnosing diabetes even over most of the the traditional factors that have always been used. The feature GWC makes use of glucose level, cholesterol level, weight and HDL level to give a more accurate foresight concerning the likelihood of the patient being diabetic or not. From analysis, GWC above 200 calls for attention since it is more likely patient is diabetic.

5 Prediction Model

In [31]:

```

X = my_features.drop(columns=['Diabetes'])
y = data['Diabetes']

X_train, X_test, y_train, y_valid = train_test_split(X, y, test_size=0.2, random_state=42)

my_model = RandomForestClassifier(n_estimators=500, max_depth=100, random_state=42)
my_model.fit(X_train, y_train)

predictions = my_model.predict(X_test)

accuracy = my_model.score(X_test, y_valid)
mse = mean_absolute_error(y_valid, predictions)

print('model accuracy:', accuracy)
print('mean absolute error:', mse)

```

model accuracy: 0.9230769230769231
mean absolute error: 0.07692307692307693

5.2 Testing the model

```
In [32]: result = model.predict([[2400,29,350,83,24,(200/39),45,200,39,0,52,170,122,75,33,170,122,75,33,170,122,75,33]])
```

```
Out[32]: array([0], dtype=int64)
```

5.3 Creating an automated diagnosing predictor

```
In [36]: import pandas as pd
import numpy as np

def get_numeric_input(prompt):
    while True:
        try:
            value = int(input(prompt))
            return value
        except ValueError:
            print("Invalid input. Please enter a numeric value.")

def predict_diabetes():
    age = get_numeric_input('Age of patient: ')
    age_sq = age ** 2
    waist = get_numeric_input('Waist size in Inches: ')
    weight = get_numeric_input('Weight of patient in lbs: ')
    sq_waist_per_age = (waist ** 2) / age
    glucose = get_numeric_input('Fasting glucose level in mg/dL: ')
    cholesterol = get_numeric_input('Cholesterol level in mg/dL: ')
    HDL = get_numeric_input('HDL Cholesterol level in mg/dL: ')
    BMI = (weight * 703) / (height ** 2)
    sq = (glucose * weight * (cholesterol / HDL))

    while True:
        try:
            gender = int(input("Gender (Input '1' for male or '0' for female)"))
            gender = int(gender)
            if gender not in ('0', '1'):
                raise ValueError
            break
        except ValueError:
            print("Invalid input. Please enter either '0' or '1'.")

    height = get_numeric_input('Height of patient in inches: ')
    BMI = 703 * (weight / (height ** 2))
    systolic_bp = get_numeric_input('Systolic Blood Pressure: ')
    diastolic_bp = get_numeric_input('Diastolic Blood Pressure: ')
    hip = get_numeric_input('Hip size in inches: ')
    waist_per_hip = waist / hip
    cholesterol_per_HDL = cholesterol / HDL

    # Forming a dataframe for the model
    data = {
        'Age_square': [age_sq],
        'Square_Waist/Age': [sq_waist_per_age],
        'BMI': [BMI],
        'systolic_bp': [systolic_bp],
        'diastolic_bp': [diastolic_bp],
        'hip': [hip],
        'waist_per_hip': [waist_per_hip],
        'cholesterol_per_HDL': [cholesterol_per_HDL],
        'gender': [gender]
    }
```

```

        'GWC': [GWC],
        'Glucose': [Glucose],
        'BMI': [BMI],
        'Chol/HDL_ratio': [cholesterol_per_HDL],
        'Age': [age],
        'Cholesterol': [cholesterol],
        'HDL Chol': [HDL],
        'Gender': [gender],
        'Height': [height],
        'Weight': [weight],
        'Systolic BP': [systolic_bp],
        'Diastolic BP': [diastolic_bp],
        'waist': [waist],
        'hip': [hip],
        'Waist/hip_ratio': [waist_per_hip]
    }

    df = pd.DataFrame(data)

    prediction = my_model.predict(df)

    if prediction == 1:
        return "This patient is likely to be diabetic."
    else:
        return "This patient is likely to be undiabetic."

result = predict_diabetes ()
print(result)

```

Age of patient: 43
 Waist size in Inches: 41
 Weight of patient in lbs: 200
 Fasting glucose level in mg/dL: 127
 Cholesterol level in mg/dL: 293
 HDL Cholesterol level in mg/dL: 60
 Gender (Input '1' for male or '0' for female): 1
 Height of patient in inches: 65
 Systolic Blood Pressure: 141
 Diastolic Blood Pressure: 97
 Hip size in inches: 39
 This patient is likely to be undiabetic.

```

In [ ]: result = predict_diabetes ()
        print (result)

```

```

In [ ]:

```