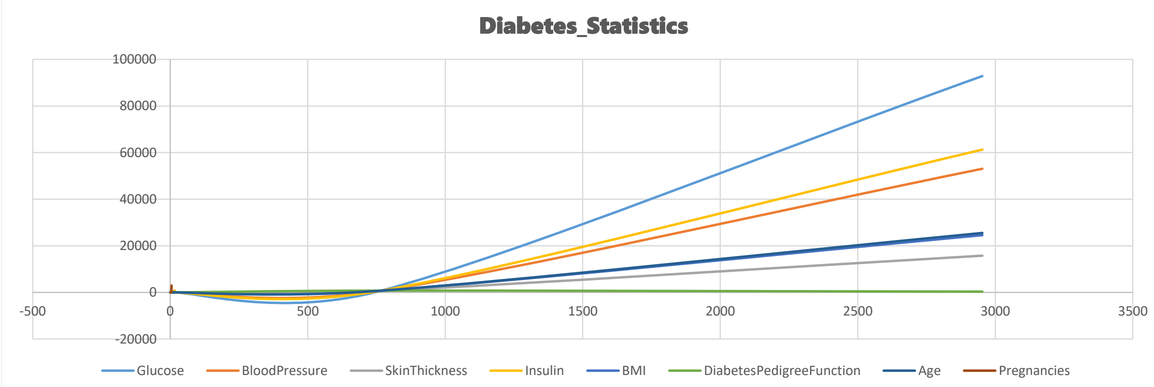
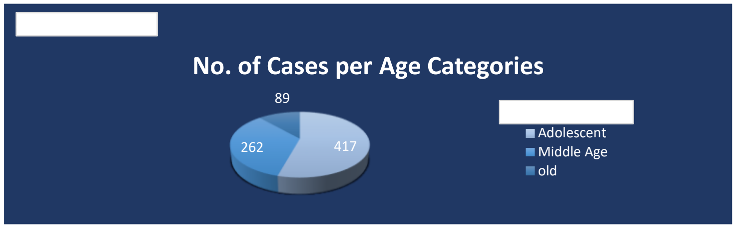
Diabetes_Statistics

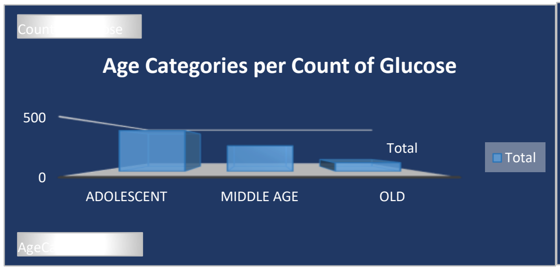
Statistics	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	SparkLine (Line)	SparkLine (Columns)
Max	17	199	122	99	846	67.1	242%	81		
Min	0	0	0	0	0	0	8%	21		
Average	3.85	120.89	69.11	20.54	79.80	31.99	47%	33.24		
Count	768	768	768	768	768	768	768	768		
Total	2,953.00	92,847.00	53,073.00	15,772.00	61,286.00	24,570.30	362.40	25,529.00		

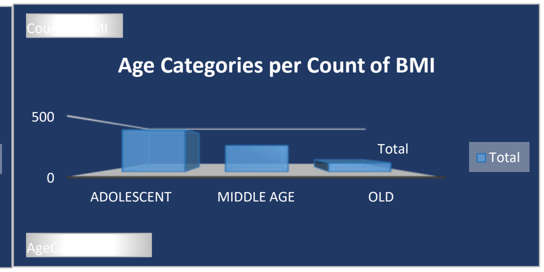


Age Categories	Count of Exist Cases
Adolescent	417
Middle Age	262
old	89
Grand Total	**768**



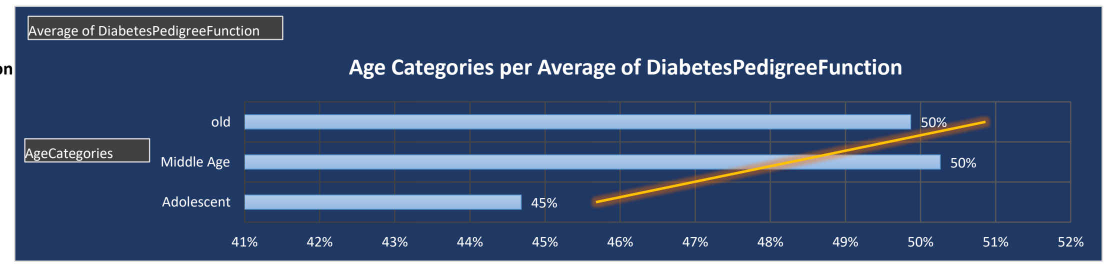
Age Categories	Count of Glucose
Adolescent	417
Middle Age	262
old	89
Grand Total	**768**



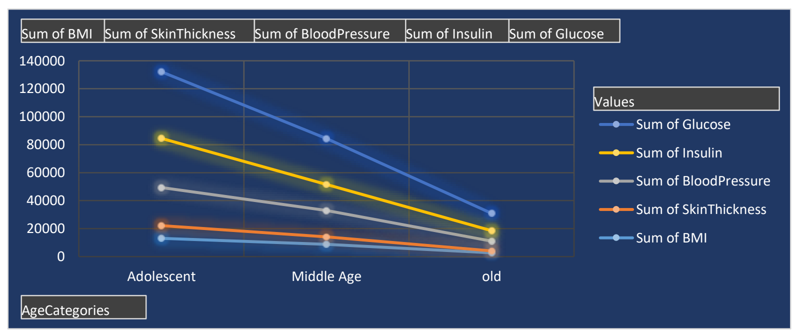


Age Categories	Count of BMI
Adolescent	417
Middle Age	262
old	89
Grand Total	**768**

Age Categories	Average of DiabetesPedigreeFunction
Adolescent	45%
Middle Age	50%
old	50%
Grand Total	**47%**

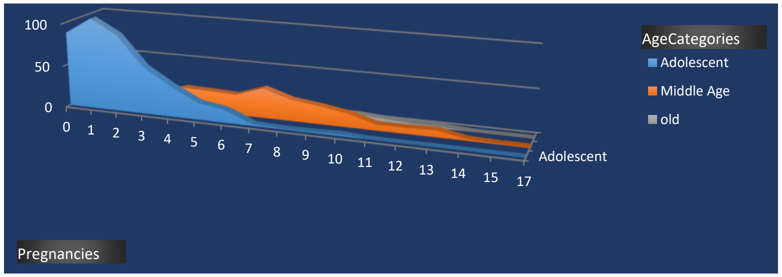


Row Labels	Sum of BMI	Sum of SkinThickness	Sum of BloodPressure	Sum of Insulin	Sum of Glucose
Adolescent	13061.3	9089	27240	35156	47611
Middle Age	8812.1	5288	18858	18643	32816
old	2696.9	1395	6975	7487	12420
Grand Total	**24570.3**	**15772**	**53073**	**61286**	**92847**



Count of Exist C	Column Labels			
Pregnancies	**Adolescent**	**Middle Age**	**old**	**Grand Total**
0	88	17	6	111
1	107	24	4	135
2	90	6	7	103

3	55	17	3	75
4	36	26	6	68
5	20	25	12	57
6	15	24	11	50
7	2	35	8	45
8	1	25	12	38
9	1	21	6	28
10	2	16	6	24
11		7	4	11
12		7	2	9
13		8	2	10
14		2		2
15		1		1
17		1		1
Grand Total	**417**	**262**	**89**	**768**



Diabetes Patients Dashboard

AgeCategories

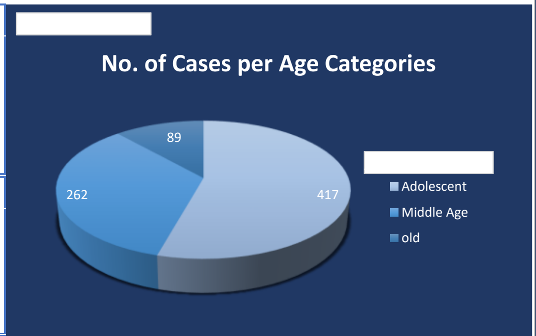
- Adolescent
- Middle Age
- old

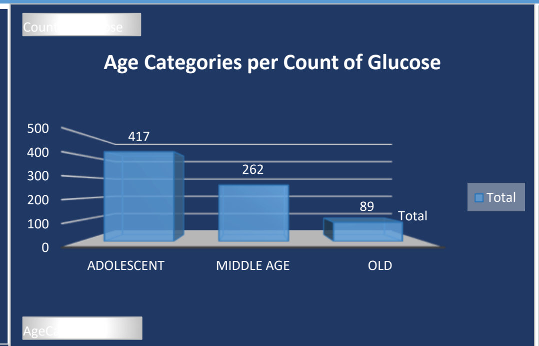
Exist Cases

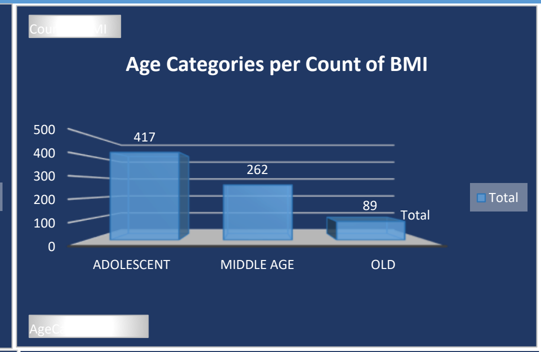
- No
- Yes

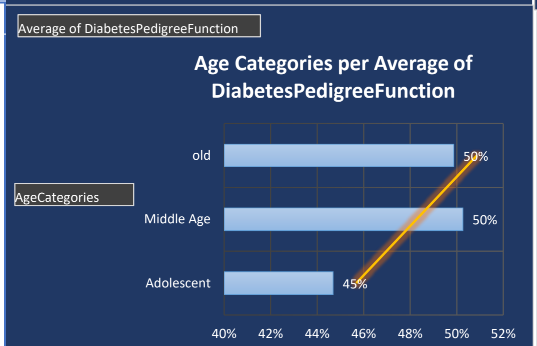
Pregnancies

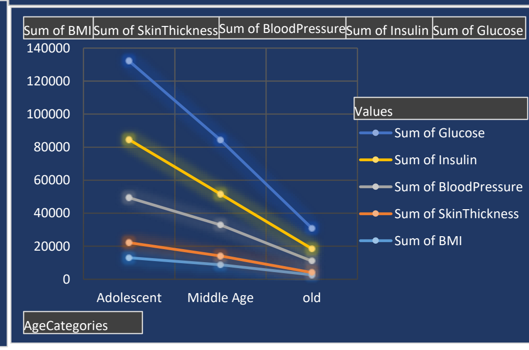
0	1
2	3
4	5
6	7
8	9
10	11
12	13
14	15
17	

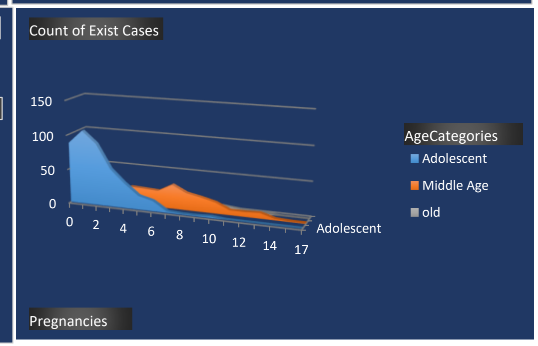








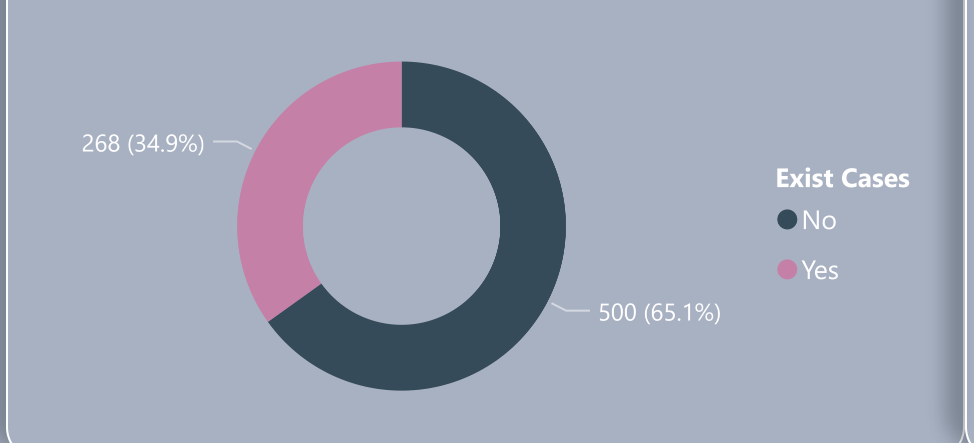




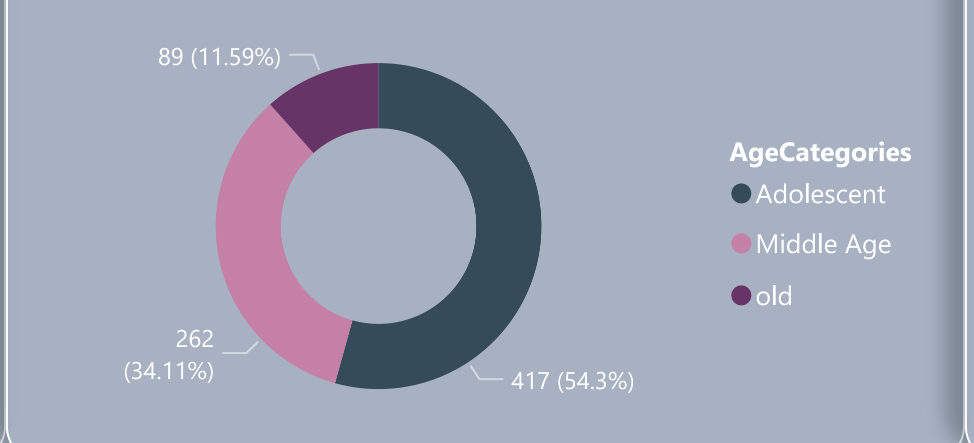
Diabetes Patients Dashboard

768	268	500	34.9%	33.24
Total Cases	Count of Injured Cases	Count of Not Injured Cases	Average of Cases	Average of Age

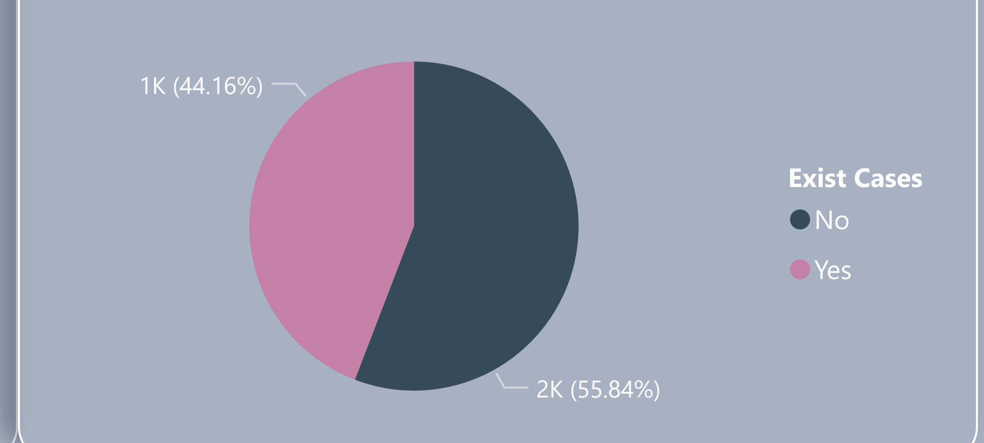
Total Exist Cases (Injured & Not Injured)



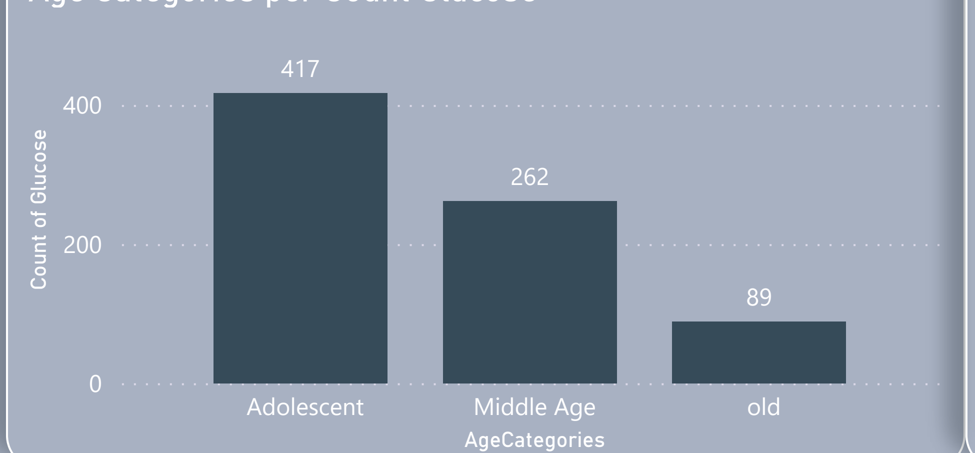
Age Categories per Total Cases



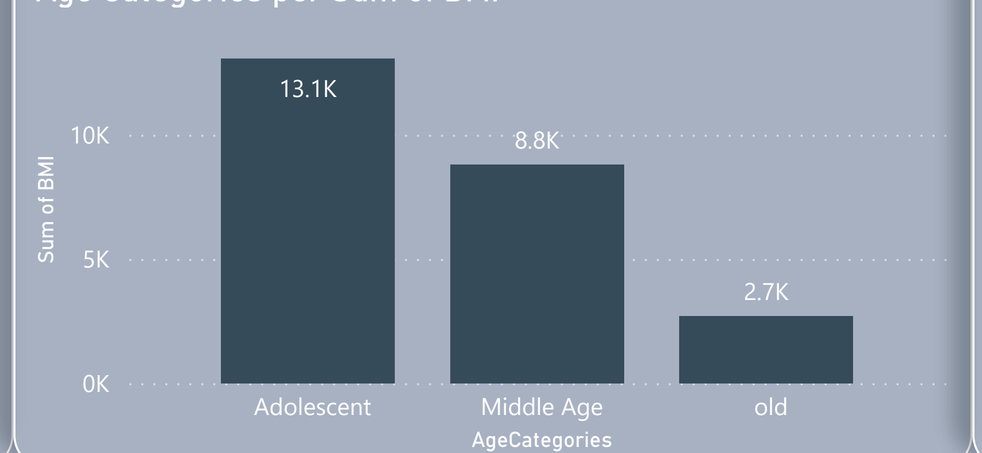
Pregnancies per Total Cases



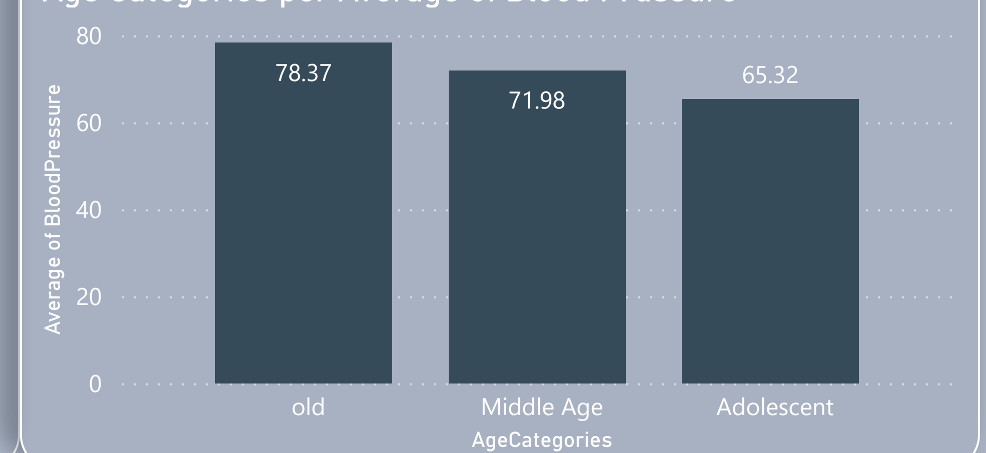
Age Categories per Count Glucose



Age Categories per Sum of BMI

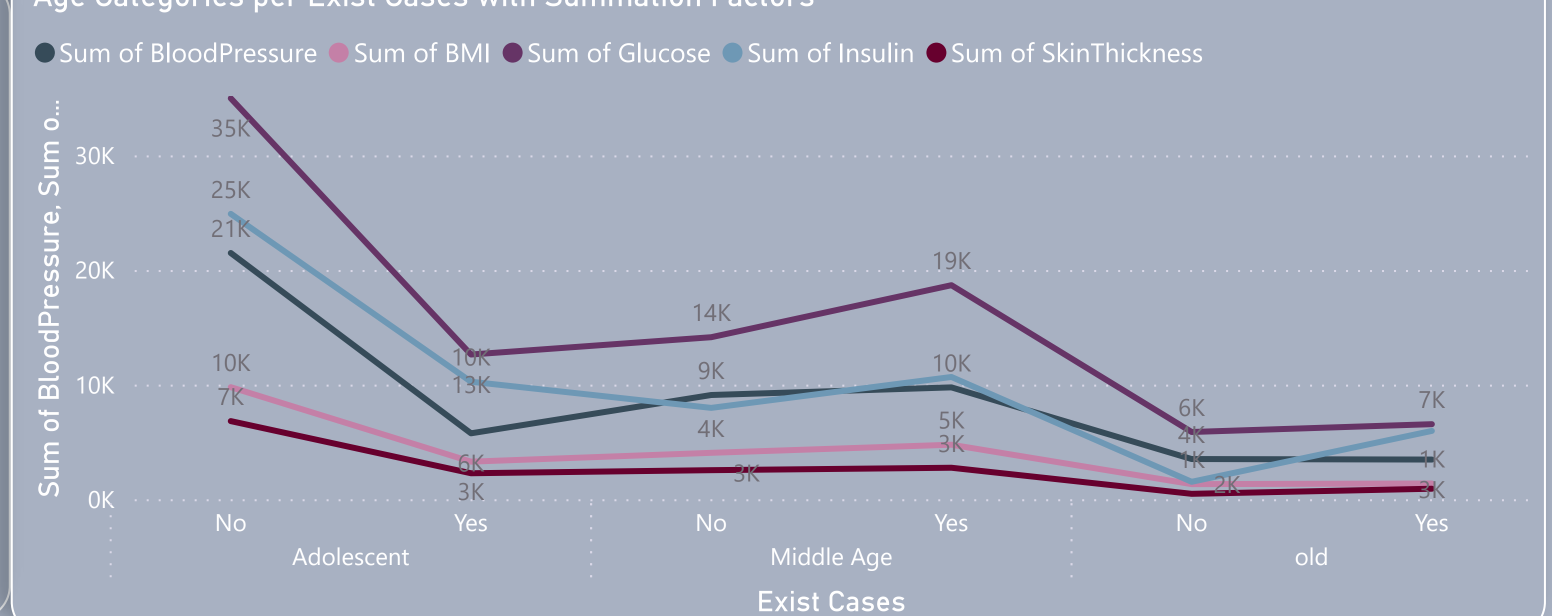


Age Categories per Average of Blood Prussure

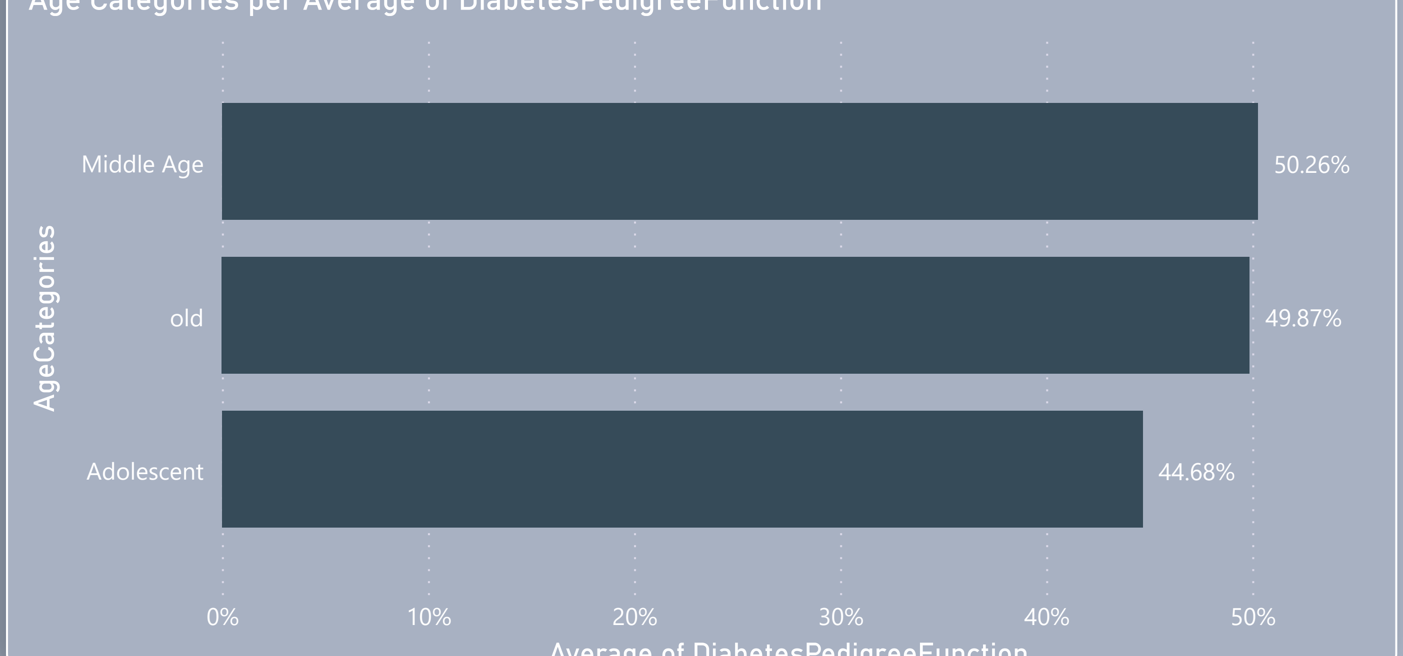


AgeCategories	Sum of BloodPressure	Sum of BMI	Sum of Glucose	Sum of Insulin	Sum of SkinThicknes
⊟ Adolescent	27,240.00	13,061.30	47,611	35,156	9,08
No	21,486.00	9,780.30	34,982	24,900	6,81
Yes	5,754.00	3,281.00	12,629	10,256	2,27
⊟ Middle Age	18,858.00	8,812.10	32,816	18,643	5,28
No	9,096.00	4,051.90	14,139	7,973	2,53
Yes	9,762.00	4,760.20	18,677	10,670	2,75
⊟ old	6,975.00	2,696.90	12,420	7,487	1,39
No	3,510.00	1,319.90	5,869	1,523	47
Yes	3,465.00	1,377.00	6,551	5,964	92
Total	53,073.00	24,570.30	92,847	61,286	15,77

Age Categories per Exist Cases with Summation Factors



Age Categories per Average of DiabetesPedigreeFunction



Total Sum of BloodPressure was higher for No (34,092.00) than Yes (18981).

Sum of BloodPressure and total Sum of BMI are positively correlated with each other.

Count of Exist Cases for No (500) was higher than Yes (268).

No accounted for 65.10% of Count of Exist Cases.

At 417, Adolescent had the highest Count of Glucose and was 368.54% higher than old, which had the lowest Count of Glucose at 89.

old had 89 Count of Glucose, Middle Age had 262, and Adolescent had 417.

Age

21 81

AgeCategories

- Adolescent
- Middle Age
- old

Exist Cases

No

Yes

Pregnancies

0, 1, 10, 2, 11, 3, 12, 4, 13, 5, 14, 6, 15, 7, 17, 8

BMI

0.00, 18.20, 20.80, 18.40, 21.00, 22.60, 19.10, 21.10, 22.70, 19.30, 21.20, 22.90, 19.40, 21.70, 23.00, 19.50, 21.80, 23.10, 19.60, 21.90, 23.20, 19.90, 22.10, 23.30, 20.00, 22.20, 23.40, 20.10, 22.30, 23.50

Diabetes Analysis

In this file we'll be analyzing Diabetes information for female.

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

%matplotlib inline
```

+ Code + Text

Reading data:

```
pd.read_excel
```

```
<function pandas.io.excel._base.read_excel(io, sheet_name: 'str | int | list[IntStrT] | None' = 0, *, header: 'int | Sequence[int] | None' = 0, names: 'list[str] | None' = None, index_col: 'int | Sequence[int] | None' = None, usecols: 'int | str | Sequence[int] | Sequence[str] | Callable[[str], bool] | None' = None, dtype: 'DtypeArg | None' = None, engine: "Literal['xlrd', 'openpyxl', 'odf', 'pyxlsb'] | None" = None, converters: 'dict[str, Callable] | dict[int, Callable] | None' = None, true_values: 'Iterable[Hashable] | None' = None, false_values: 'Iterable[Hashable] | None' = None, skiprows: 'Sequence[int] | int | Callable[[int], object] | None' = None, nrows: 'int | None' = None, na_values=None, keep_default_na: 'bool' = True, na_filter: 'bool' = True, verbose: 'bool' = False, parse_dates: 'list | dict | bool' = False, date_parser: 'Callable | lib.NoDefault' = <no_default>, date_format: 'dict[Hashable, str] | str | None' = None, thousands: 'str | None' = None, decimal: 'str' = '.', comment: 'str | None' = None, skipfooter: 'int' = 0, storage_options: 'StorageOptions' = None, dtype_backend: 'DtypeBackend | lib.NoDefault' = <no_default>) -> 'DataFrame | dict[IntStrT, DataFrame]'>
```

```
df = pd.read_excel('E:\MeriSkillInternship\Project 2 - Diabetes Data\diabetes_python.xlsx')
```

```
df.head()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	AgeCategories	Exist Cases	Cases_Num	Preg
0	6	148	72	35	0	33.6	0.627	50	old	Yes	1	
1	1	85	66	29	0	26.6	0.351	31	Middle Age	No	0	
2	8	183	64	0	0	23.3	0.672	32	Middle Age	Yes	1	
3	1	89	66	23	94	28.1	0.167	21	Adolescent	No	0	
4	0	137	40	35	168	43.1	2.288	33	Middle Age	Yes	1	

```
df.shape
```

```
(768, 11)
```

```
df.tail(3)
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	AgeCategories	Exist Cases	Cases_N
765	5	121	72	23	112	26.2	0.245	30	Adolescent	No	
766	1	126	60	0	0	30.1	0.349	47	Middle Age	Yes	
767	1	93	70	31	0	30.4	0.315	23	Adolescent	No	

```
df.head()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	AgeCategories	Exist Cases	Cases_Nur
0	6	148	72	35	0	33.6	0.627	50	old	Yes	1
1	1	85	66	29	0	26.6	0.351	31	Middle Age	No	C
2	8	183	64	0	0	23.3	0.672	32	Middle Age	Yes	1
3	1	89	66	23	94	28.1	0.167	21	Adolescent	No	C
4	0	137	40	35	168	43.1	2.288	33	Middle Age	Yes	1

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 11 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   AgeCategories             768 non-null    object
 9   Exist Cases               768 non-null    object
 10  Cases_Num                 768 non-null    int64
dtypes: float64(2), int64(7), object(2)
memory usage: 66.1+ KB
```

```
df.describe()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Cases_Num
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

```
df.columns
```

```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'AgeCategories',
       'Exist Cases', 'Cases_Num'],
      dtype='object')
```

Check Null Values

```
df.isna().sum()
```

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
AgeCategories               0
Exist Cases                 0
Cases_Num                   0
dtype: int64
```

Check Duplicate Values

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

```
0
```

Numerical analysis and visualization

We'll analyze the `Glucose` column:

```
df['Glucose'].describe()
```

```
count    768.000000
mean     120.894531
std       31.972618
min        0.000000
25%       99.000000
50%      117.000000
75%      140.250000
max      199.000000
Name: Glucose, dtype: float64
```

```
df['Glucose'].mean()
```

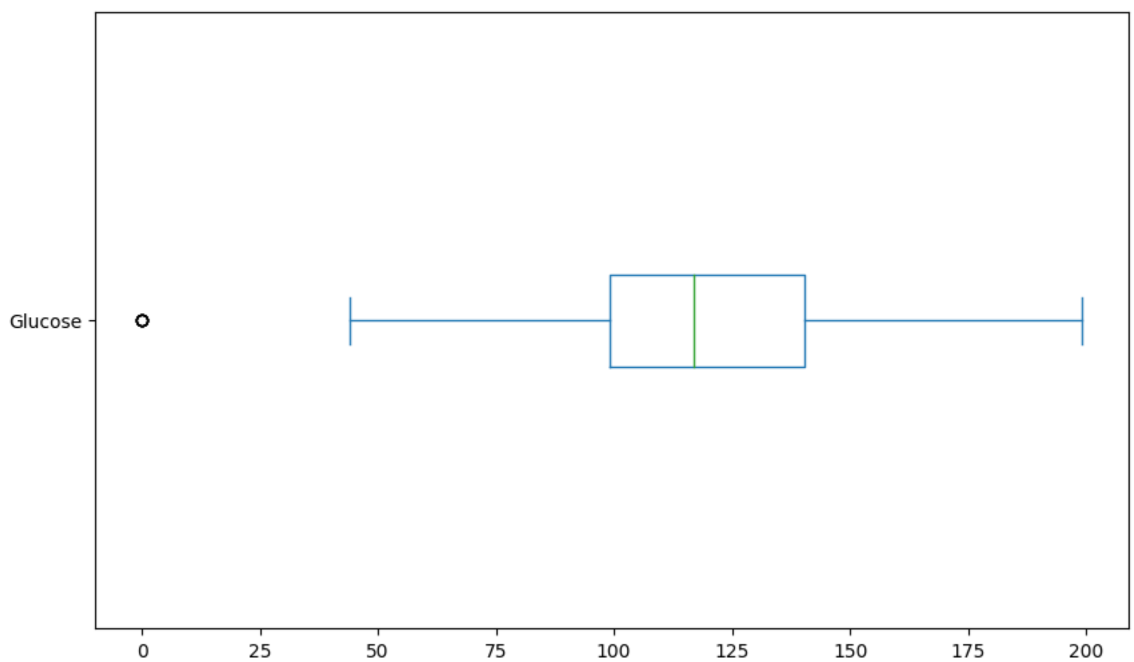
```
120.89453125
```

```
df['Glucose'].median()
```

```
117.0
```

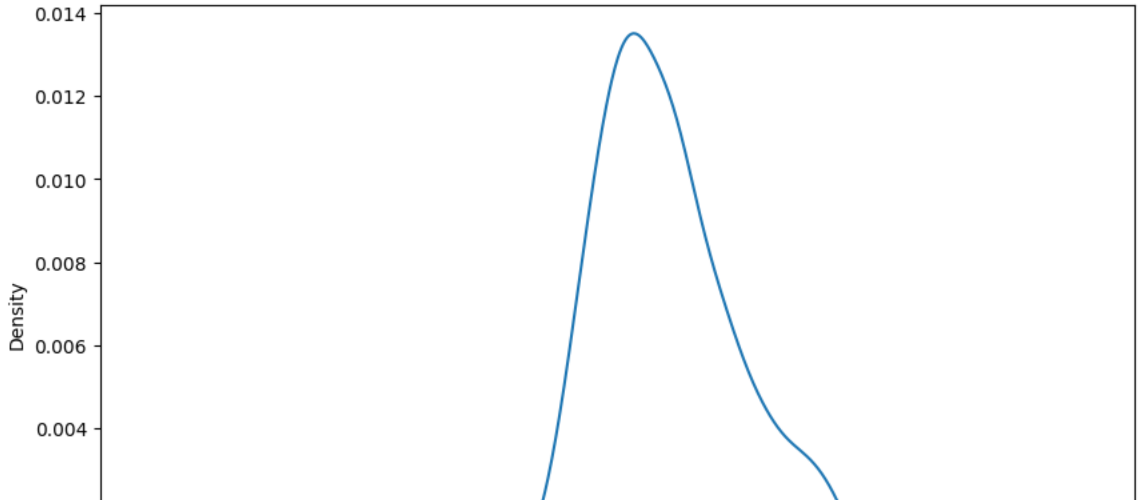
```
df['Glucose'].plot(kind='box', vert=False, figsize=(10,6))
```

```
<Axes: >
```



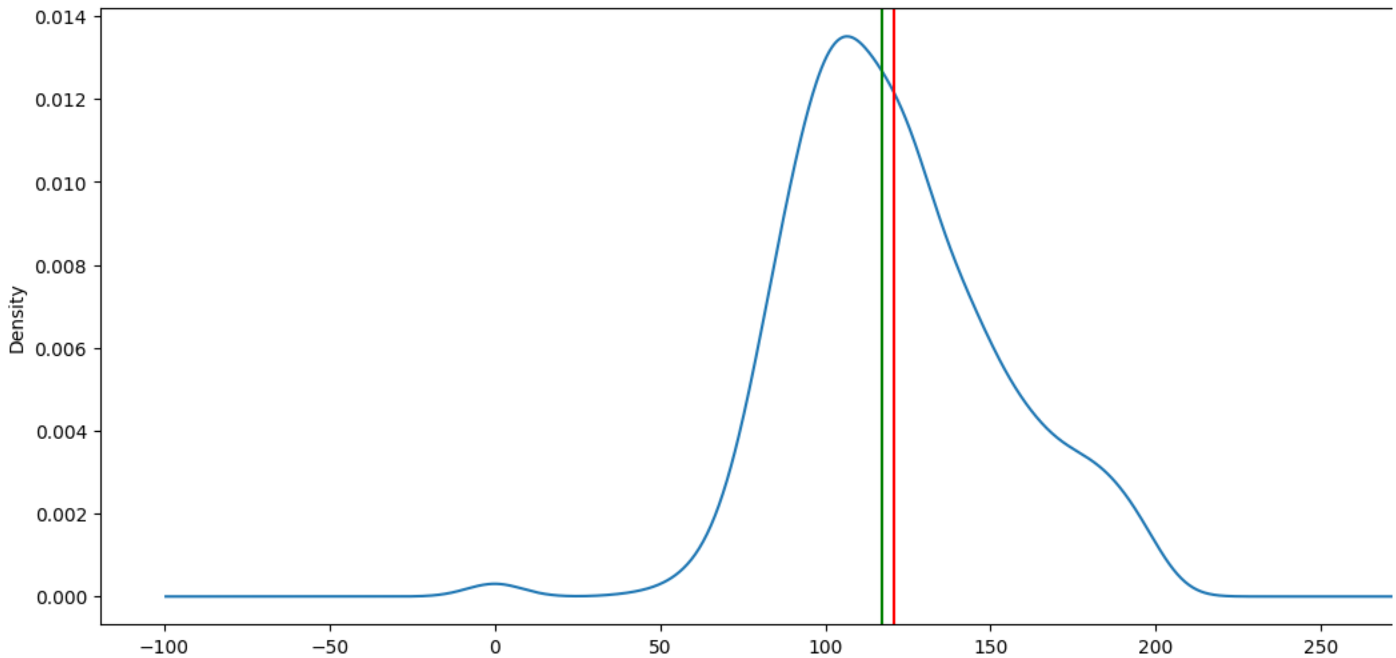

```
df['Glucose'].plot(kind='density', figsize=(10,6))
```

```
<Axes: ylabel='Density'>
```



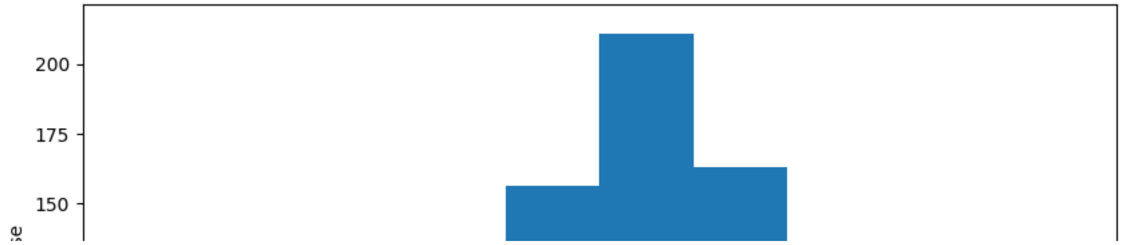

```
ax = df['Glucose'].plot(kind='density', figsize=(14,6)) # kde
ax.axvline(df['Glucose'].mean(), color='red')
ax.axvline(df['Glucose'].median(), color='green')
```

```
<matplotlib.lines.Line2D at 0x1c9b939e2d0>
```




```
ax = df['Glucose'].plot(kind='hist', figsize=(10,6))
ax.set_ylabel('Number of Glucose')
ax.set_xlabel('Glucose')
```

```
Text(0.5, 0, 'Glucose')
```



Categorical analysis and visualization

We'll analyze the `AgeCategories` column:

```
df.head()
```

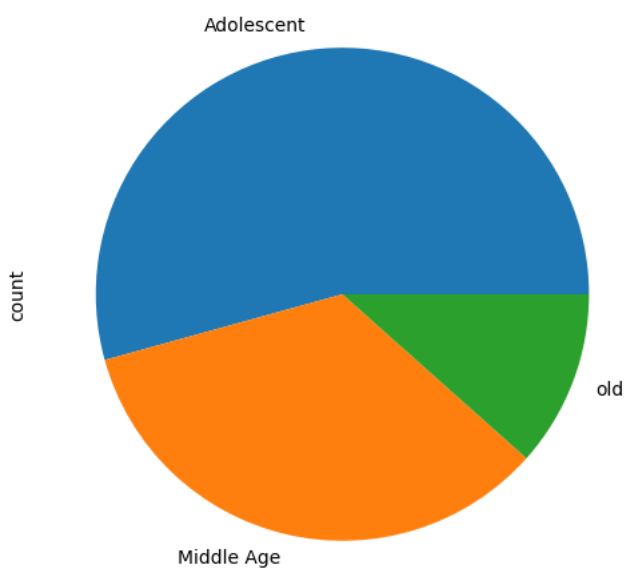
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	AgeCategories	Exist Cases	Cases_Num
0	6	148	72	35	0	33.6	0.627	50	old	Yes	1
1	1	85	66	29	0	26.6	0.351	31	Middle Age	No	0
2	8	183	64	0	0	23.3	0.672	32	Middle Age	Yes	1
3	1	89	66	23	94	28.1	0.167	21	Adolescent	No	0
4	0	137	40	35	168	43.1	2.288	33	Middle Age	Yes	1

```
df['AgeCategories'].value_counts()
```

```
AgeCategories
Adolescent    417
Middle Age    262
old            89
Name: count, dtype: int64
```

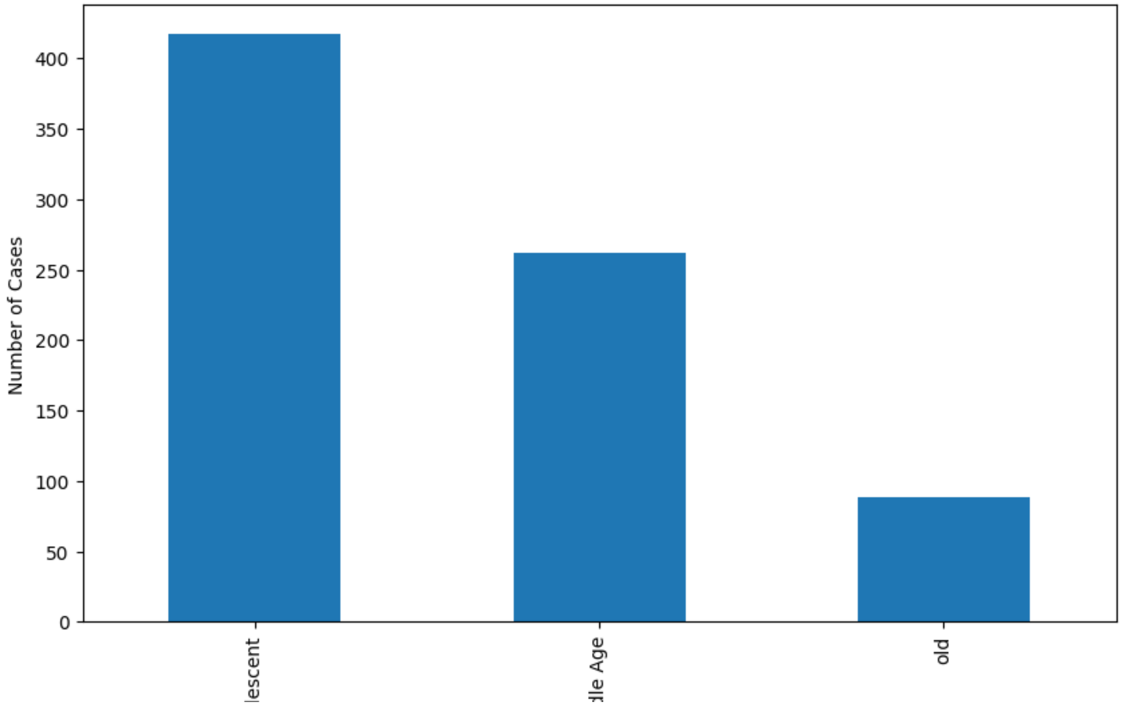
```
df['AgeCategories'].value_counts().plot(kind='pie', figsize=(6,6))
```

```
<Axes: ylabel='count'>
```



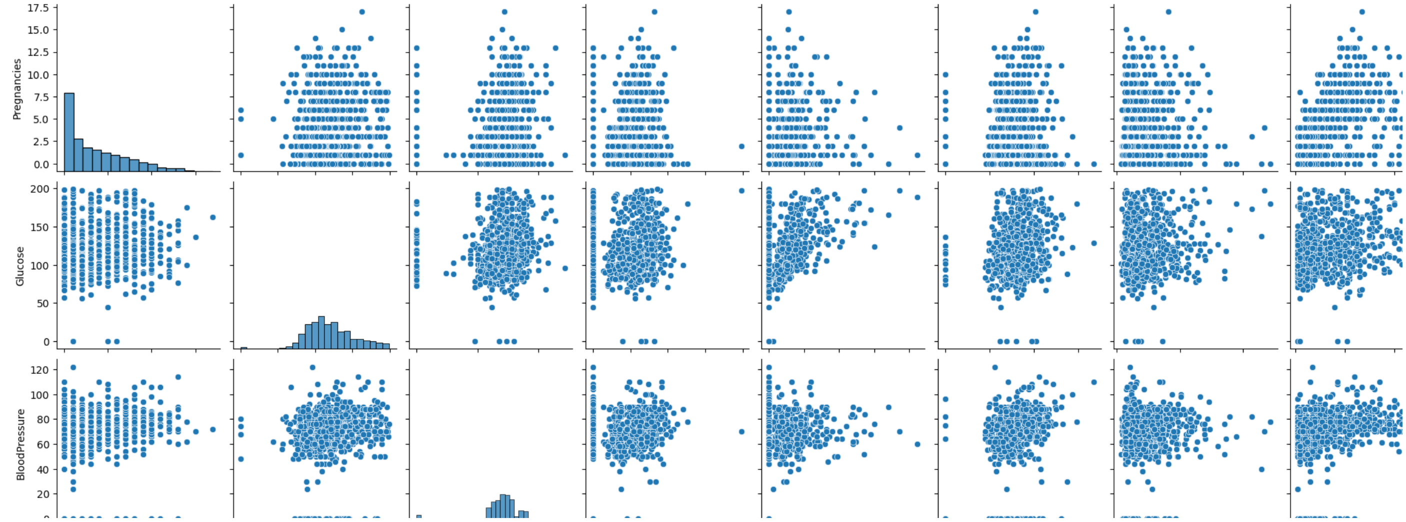

```
ax = df['AgeCategories'].value_counts().plot(kind='bar', figsize=(10,6))
ax.set_ylabel('Number of Cases')
```

```
Text(0, 0.5, 'Number of Cases')
```




```
sns.pairplot(df)
plt.show()
```

```
c:\Users\USER\AppData\Local\Programs\Python\Python311\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layout has chang
  self._figure.tight_layout(*args, **kwargs)
```



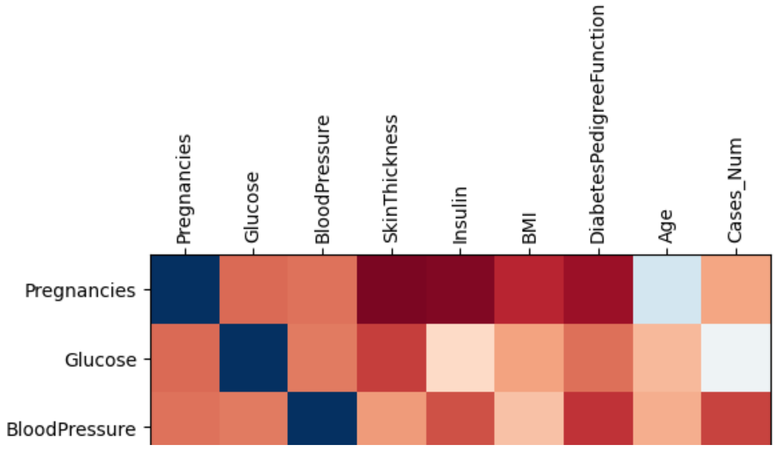
Relationship between the columns?

We will find any significant relationship

```
columns = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
       'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age', 'Cases_Num']
corr=df[columns].corr()
corr
```

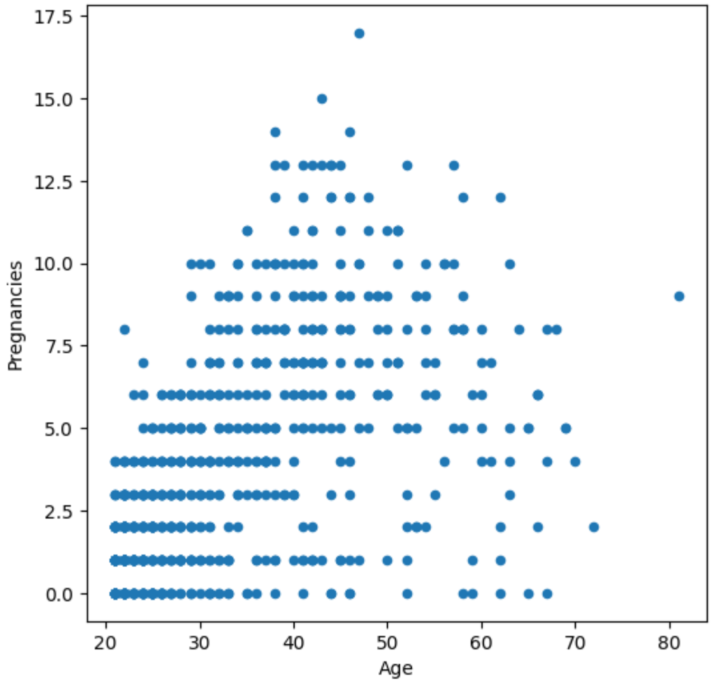
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Cas
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.017683	-0.033523	0.544341	0.2
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.221071	0.137337	0.263514	0.4
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.281805	0.041265	0.239528	0.0
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	0.183928	-0.113970	0.0
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.197859	0.185071	-0.042163	0.1
BMI	0.017683	0.221071	0.281805	0.392573	0.197859	1.000000	0.140647	0.036242	0.2
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928	0.185071	0.140647	1.000000	0.033561	0.1
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.036242	0.033561	1.000000	0.2
Cases_Num	0.221898	0.466581	0.065068	0.074752	0.130548	0.292695	0.173844	0.238356	1.0

```
fig = plt.figure(figsize=(6,6))
plt.matshow(corr, cmap='RdBu', fignum=fig.number)
plt.xticks(range(len(corr.columns)), corr.columns, rotation='vertical');
plt.yticks(range(len(corr.columns)), corr.columns);
```



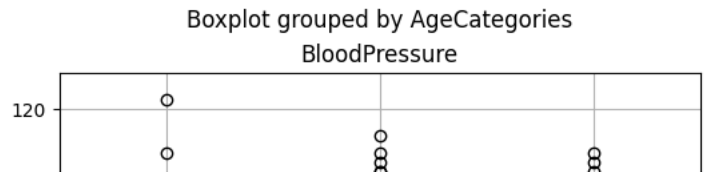

```
df.plot(kind='scatter', x='Age', y='Pregnancies', figsize=(6,6))
```

```
<Axes: xlabel='Age', ylabel='Pregnancies'>
```



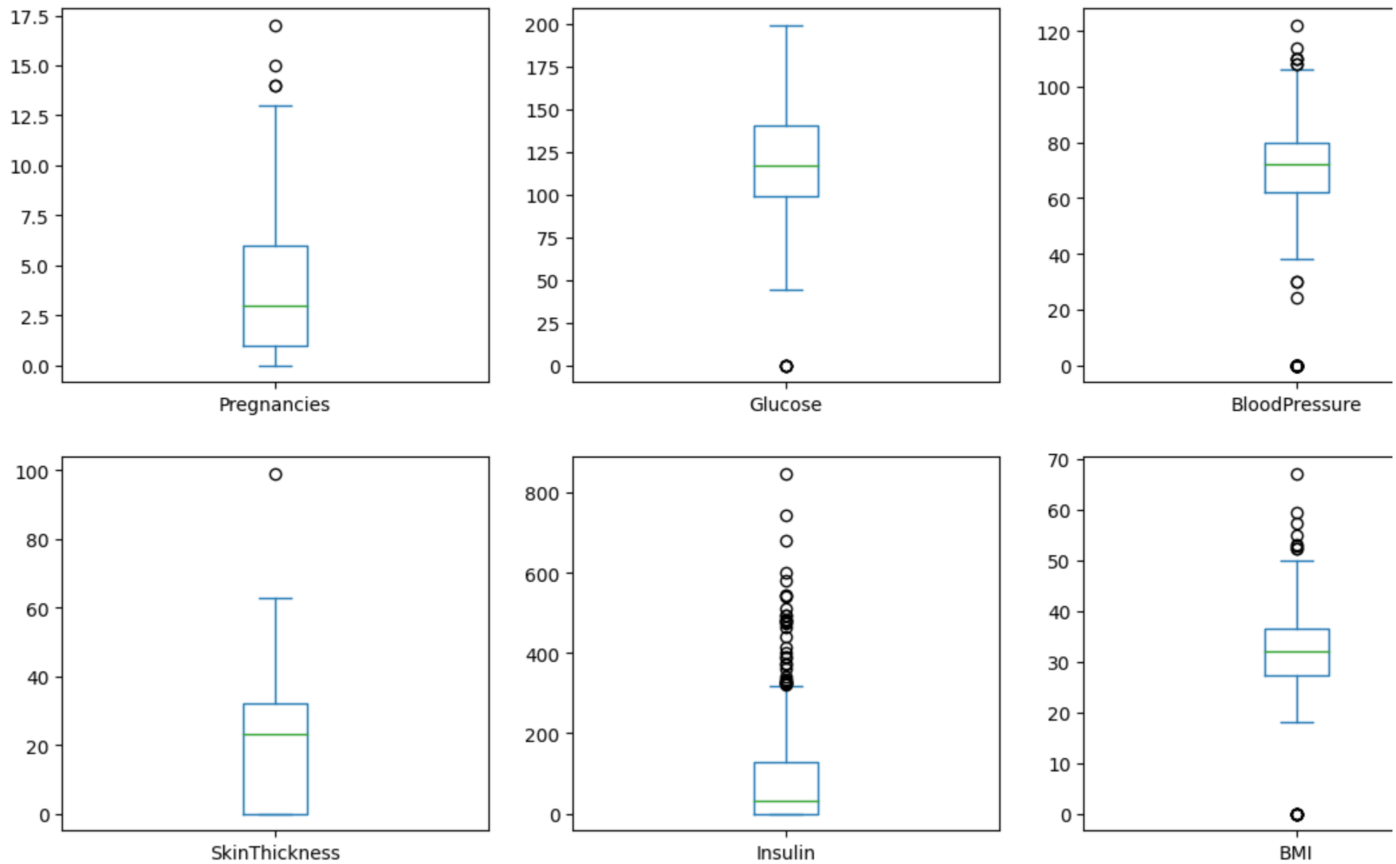

```
ax = df[['BloodPressure', 'AgeCategories']].boxplot(by='AgeCategories', figsize=(6,6))
ax.set_ylabel('BloodPressure')
```

```
Text(0, 0.5, 'BloodPressure')
```




```
boxplot_cols = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness','Insulin', 'BMI']
df[boxplot_cols].plot(kind='box', subplots=True, layout=(2,3), figsize=(14,8))
```

```
Pregnancies        Axes(0.125,0.53;0.227941x0.35)
Glucose         Axes(0.398529,0.53;0.227941x0.35)
BloodPressure   Axes(0.672059,0.53;0.227941x0.35)
SkinThickness      Axes(0.125,0.11;0.227941x0.35)
Insulin         Axes(0.398529,0.11;0.227941x0.35)
BMI             Axes(0.672059,0.11;0.227941x0.35)
dtype: object
```



Column wrangling

Add and calculate a new `Pregnancies_per_Age` column

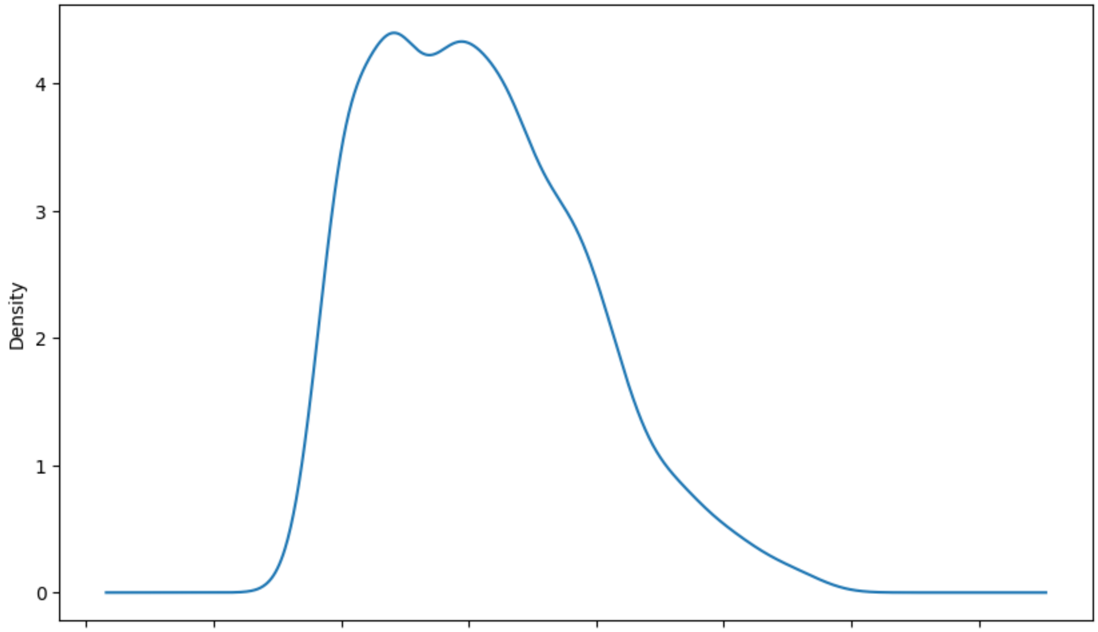
```
df['Pregnancies_per_Age'] = df['Pregnancies'] / df['Age']
```

```
df['Pregnancies_per_Age'].head()
```

```
0    0.120000
1    0.032258
2    0.250000
3    0.047619
4    0.000000
Name: Pregnancies_per_Age, dtype: float64
```

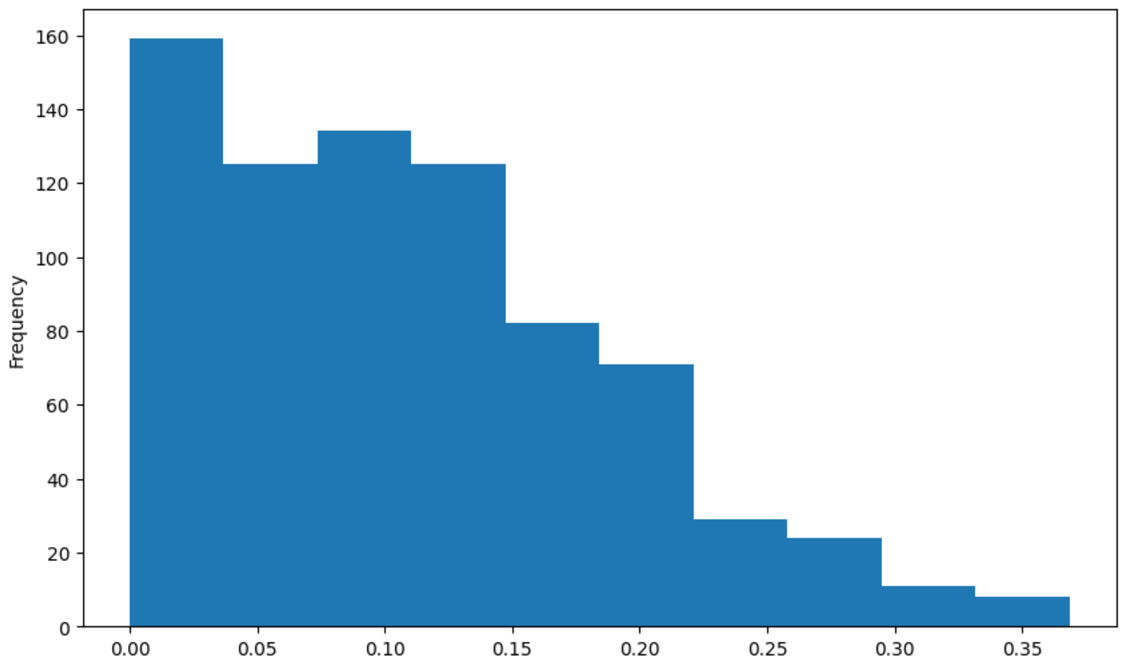
```
df['Pregnancies_per_Age'].plot(kind='density', figsize=(10,6))
```

```
<Axes: ylabel='Density'>
```




```
df['Pregnancies_per_Age'].plot(kind='hist', figsize=(10,6))
```

```
<Axes: ylabel='Frequency'>
```



Add and calculate a new `Calculated_Insulin` column

Use this formula

$$Calculated_Insulin = Insulin * DiabetesPedigreeFunction$$

```
df['Calculated_Insulin'] = df['Insulin'] * df['DiabetesPedigreeFunction']
```

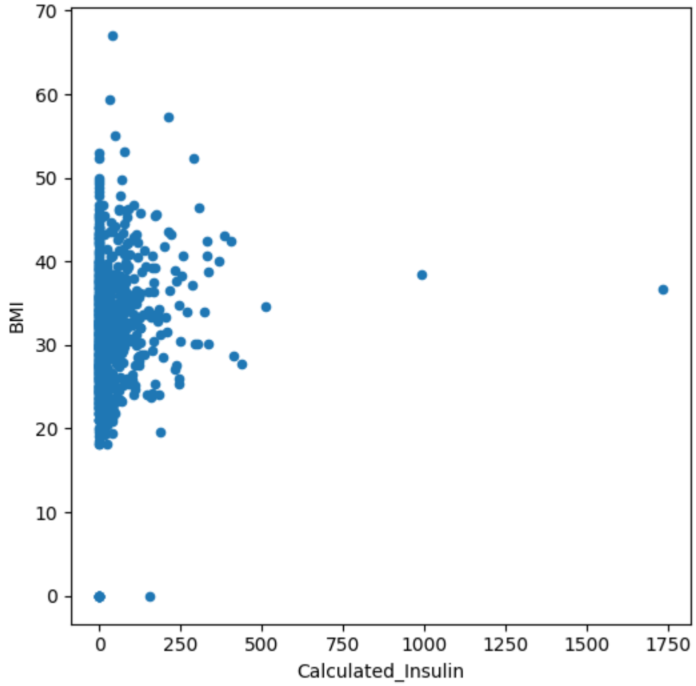
```
df['Calculated_Insulin'].head()
```

```
0      0.000
1      0.000
2      0.000
3     15.698
4    384.384
Name: Calculated_Insulin, dtype: float64
```

We can see the relationship between `Cost` and `Profit` using a scatter plot:

```
df.plot(kind='scatter', x='Calculated_Insulin', y='BMI', figsize=(6,6))
```

<Axes: xlabel='Calculated_Insulin', ylabel='BMI'>



Selection & Indexing:

Get all the data which related to age category `old`

```
df.loc[df['AgeCategories'] == 'old']
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	AgeCategories	Exist Cases	Cases_Num	Pr
0	6	148	72	35	0	33.6	0.627	50	old	Yes	1	
8	2	197	70	45	543	30.5	0.158	53	old	Yes	1	
9	8	125	96	0	0	0.0	0.232	54	old	Yes	1	
12	10	139	80	0	0	27.1	1.441	57	old	No	0	
13	1	189	60	23	846	30.1	0.398	59	old	Yes	1	
...	...	...	...	...	...	...	...	...	...	...	...	
734	2	105	75	0	0	23.3	0.560	53	old	No	0	
749	6	162	62	0	0	24.3	0.178	50	old	Yes	1	
757	0	123	72	0	0	36.3	0.258	52	old	Yes	1	
759	6	190	92	0	0	35.5	0.278	66	old	Yes	1	
763	10	101	76	48	180	32.9	0.171	63	old	No	0	

89 rows × 13 columns

Get the mean SkinThickness of the `Middle 1age (31-49)`

```
df.loc[df['AgeCategories'] == 'Middle Age', 'SkinThickness'].mean()
```

```
20.18320610687023
```

How many records belong to Age Group `Adolescent (<31)` or `Middle Age (31-49)`?

```
df.loc[(df['AgeCategories'] == 'Adolescent') | (df['AgeCategories'] == 'Middle Age')].shape[0]
```

```
679
```

Get the mean BMI for `Adolescent (<31)` which is injured in diabete `Exist Cases = yes`

```
df.loc[(df['AgeCategories'] == 'Adolescent') & (df['Exist Cases'] == 'Yes'), 'BMI'].mean()
```

```
36.455555555555556
```