In [1]: import pandas as pd
 from matplotlib import pyplot as plt
 %matplotlib inline
 from sklearn.model_selection import train_test_split
 from sklearn.linear_model import LogisticRegression
 from sklearn.metrics import accuracy_score
 import numpy as np
 import seaborn as sns
 import os

In [2]: df=pd.read_csv(r'C:\Users\ashuk\Downloads\diabetes.csv')

In [3]: df #ASHU PANDIT

Out[3]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFun
0	6	148	72	35	0	33.6	(
1	1	85	66	29	0	26.6	(
2	8	183	64	0	0	23.3	(
3	1	89	66	23	94	28.1	(
4	0	137	40	35	168	43.1	1
					•••		
763	10	101	76	48	180	32.9	(
764	2	122	70	27	0	36.8	(
765	5	121	72	23	112	26.2	(
766	1	126	60	0	0	30.1	(
767	1	93	70	31	0	30.4	(

768 rows × 9 columns

<bound meth<="" th=""><th>nod NDFra</th><th>me.head of</th><th></th><th>Pregnancies</th><th>Glucose</th><th>BloodPre</th><th>ssure</th></bound>	nod NDFra	me.head of		Pregnancies	Glucose	BloodPre	ssure
nThickness	Insulin	BMI \					
0	6	148		72	35	0	33.6
1	1	85		66	29	0	26.6
2	8	183		64	0	0	23.3
3	1	89		66	23	94	28.1
4	0	137		40	35	168	43.1
• •	• • •	• • •		• • •	• • •	• • •	
763	10	101		76	48	180	32.9
764	2	122		70	27	0	36.8
765	5	121		72	23	112	26.2
766	1	126		60	0	0	30.1
767	1	93		70	31	0	30.4
Diabet	tesPedign	eeFunction	Age	Outcome			
0		0.627	50	1			
1		0.351	31	0			
2		0.672	32	1			
3		0.167	21	0			
4		2.288	33	1			
			• • •	• • •			
763		0.171	63	0			
764		0.340	27	0			
765		0.245	30	0			
766		0.349	47	1			
767		0.315	23	0			

In [5]: df.head()

Out[5]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFuncti
0	6	148	72	35	0	33.6	0.6
1	1	85	66	29	0	26.6	0.3
2	8	183	64	0	0	23.3	0.6
3	1	89	66	23	94	28.1	0.1
4	0	137	40	35	168	43.1	2.2
4							—

In [6]: df.tail()

Out[6]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	вмі	DiabetesPedigreeFun
763	10	101	76	48	180	32.9	(
764	2	122	70	27	0	36.8	(
765	5	121	72	23	112	26.2	(
766	1	126	60	0	0	30.1	(
767	1	93	70	31	0	30.4	(
4							

In [7]: df.describe()

Out[7]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	Diab€
count	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	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	
1							•

In [8]: df.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

In []:

```
In [9]:
           df.isnull()
 Out[9]:
                             Glucose BloodPressure SkinThickness Insulin
                                                                             BMI DiabetesPedigreeFui
                 Pregnancies
              0
                                                                            False
                       False
                                False
                                               False
                                                              False
                                                                      False
                                               False
              1
                       False
                                False
                                                              False
                                                                      False False
              2
                       False
                                False
                                               False
                                                              False
                                                                      False False
              3
                       False
                                False
                                               False
                                                              False
                                                                      False False
              4
                       False
                                False
                                               False
                                                              False
                                                                      False False
            763
                       False
                                False
                                               False
                                                              False
                                                                      False False
            764
                       False
                                False
                                               False
                                                              False
                                                                      False False
            765
                       False
                                False
                                               False
                                                              False
                                                                      False False
            766
                       False
                                               False
                                                              False
                                                                      False False
                                False
            767
                       False
                                False
                                               False
                                                              False
                                                                      False False
           768 rows × 9 columns
In [10]: df.isnull().sum()
Out[10]: Pregnancies
                                            0
                                            0
           Glucose
           BloodPressure
                                            0
           SkinThickness
                                            0
           Insulin
                                            0
           BMI
                                            0
           DiabetesPedigreeFunction
                                            0
           Age
                                            0
                                            0
           Outcome
           dtype: int64
In [11]: | df.isnull().sum().sum()
Out[11]: 0
In [12]:
          df.shape
Out[12]: (768, 9)
```

In [13]:	df.value_counts()									
Out[13]:			Glucose tion Age		SkinThickness	Insulin	BMI	Diabetes		
	0		57	60	0	0	21.7	0.735		
	67	0	1 67	76	0	0	45.3	0.194		
	46	0	1	, 0	0	O	73.3	0.154		
	5		103	108	37	0	39.2	0.305		
	65	0	1 104	74	0	0	28.8	0.153		
	48	0	1			Ü	20.0	0.133		
	20	0	105	72	29	325	36.9	0.159		
	28	0	1							
	• •									
	2 21	0	84 1	50	23	76	30.4	0.968		
	21	V	85	65	0	0	39.6	0.930		
	27	0	1							
	25	0	87 1	0	23	0	28.9	0.773		
	23	V	1	58	16	52	32.7	0.166		
	25	0	1							
	17	4	163	72	41	114	40.9	0.817		
	47 Leng	1 +h· 768	1 dtype: i	nt64						
	Leng	,	acype. I	1100-1						

In [14]: df.columns

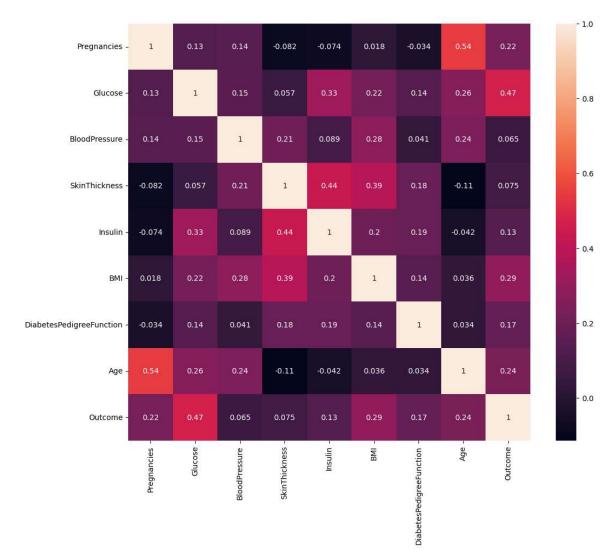
In [15]: df.corr()

Out[15]:

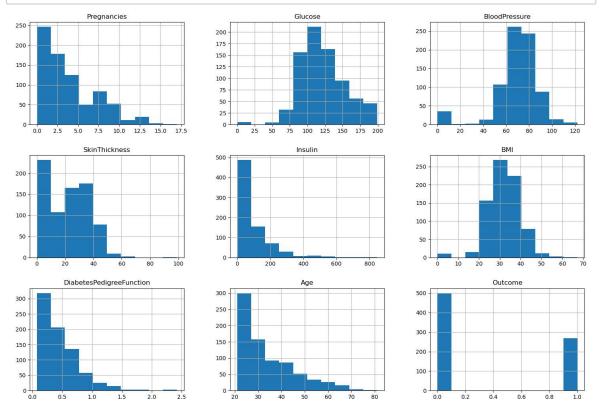
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.
ВМІ	0.017683	0.221071	0.281805	0.392573	0.197859	1.
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928	0.185071	0.
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.
Outcome	0.221898	0.466581	0.065068	0.074752	0.130548	0.

```
In [16]: plt.figure(figsize = (12,10))
sns.heatmap(df.corr(),annot = True)
```

Out[16]: <Axes: >



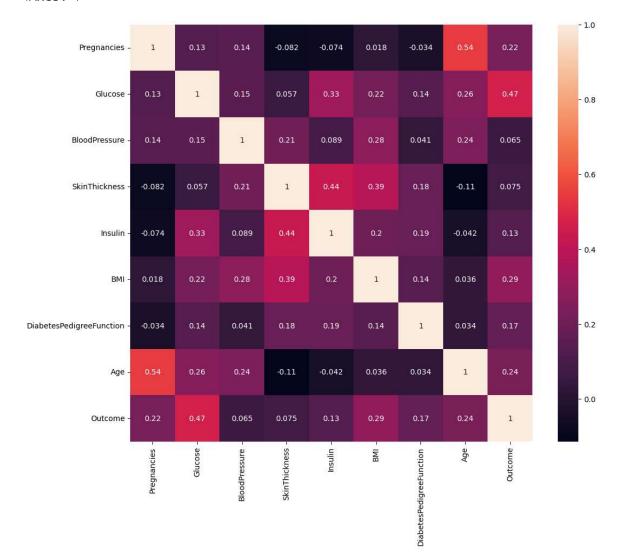
In [17]: df.hist(figsize=(18,12))
 plt.show()



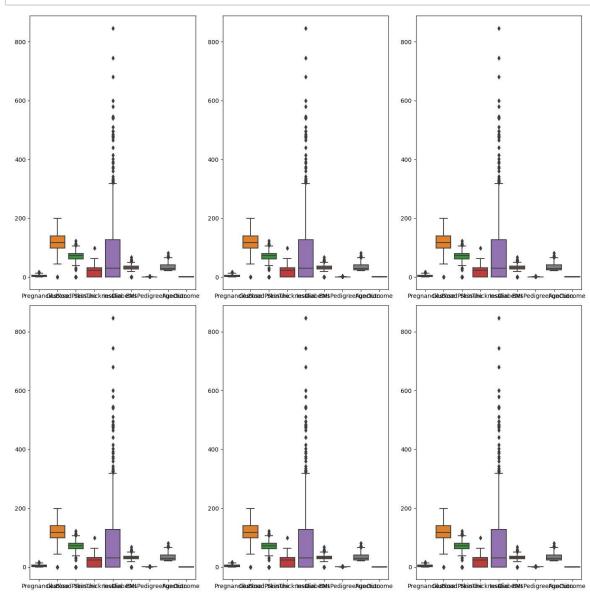
```
In [18]: features = ['Glucose', 'BloodPressure', 'Insulin', 'BMI', 'Age','SkinThickne
    plt.figure(figsize=(14, 10))
    for i, feature in enumerate(features, start=1):
        plt.subplot(2, 3, i)
        sns.boxplot(x=feature, data=df)
    plt.tight_layout()
    plt.show()
```

```
In [19]: plt.figure(figsize = (12,10))
sns.heatmap(df.corr(), annot =True)
```

Out[19]: <Axes: >



```
In [22]: features = ['Glucose', 'BloodPressure', 'Insulin', 'BMI', 'Age', 'SkinThickne
    plt.figure(figsize=(14, 14))
    for i, feature in enumerate(features, start=1):
        plt.subplot(2, 3, i)
        sns.boxplot(df)
    plt.tight_layout()
    plt.show()
```

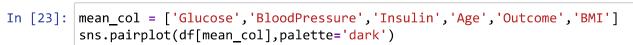


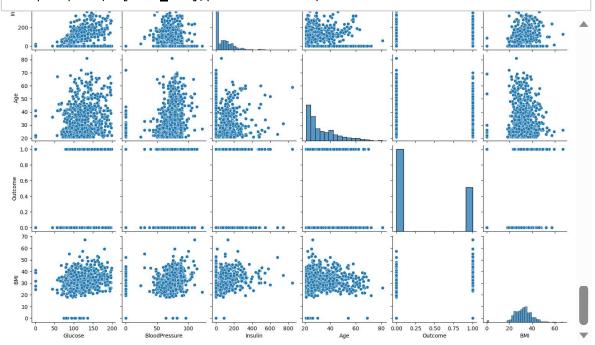
In [21]: df

Out[21]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFun
0	6	148	72	35	0	33.6	(
1	1	85	66	29	0	26.6	(
2	8	183	64	0	0	23.3	(
3	1	89	66	23	94	28.1	(
4	0	137	40	35	168	43.1	1
					•••		
763	10	101	76	48	180	32.9	(
764	2	122	70	27	0	36.8	(
765	5	121	72	23	112	26.2	(
766	1	126	60	0	0	30.1	(
767	1	93	70	31	0	30.4	(

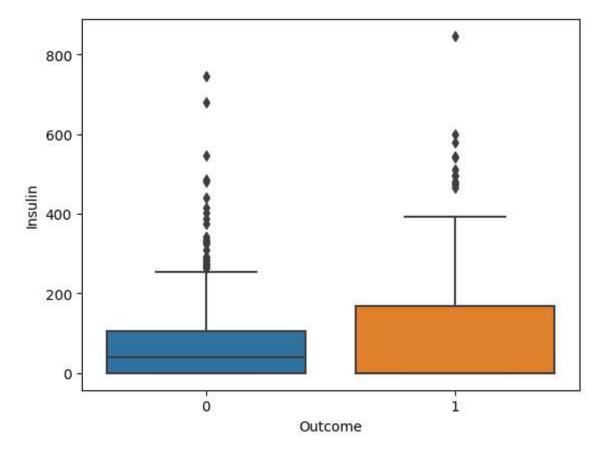
768 rows × 9 columns





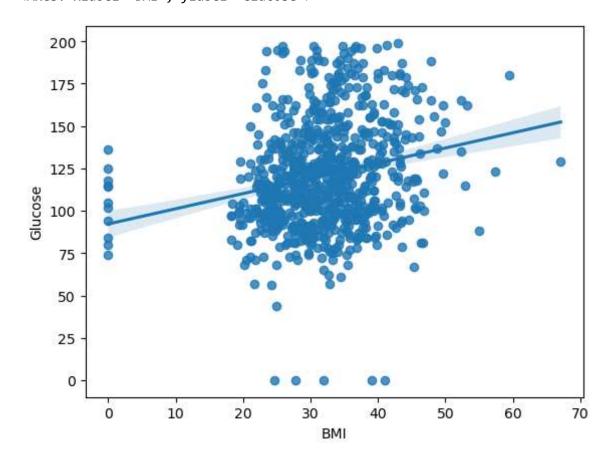
```
In [24]: sns.boxplot(x='Outcome',y='Insulin',data=df)
```

Out[24]: <Axes: xlabel='Outcome', ylabel='Insulin'>



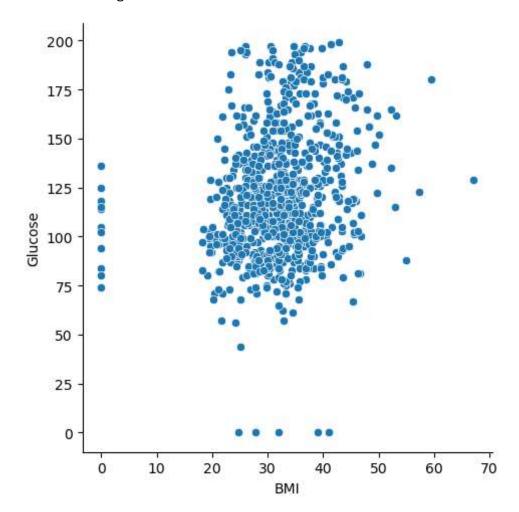
In [25]: sns.regplot(x='BMI', y= 'Glucose', data=df)

Out[25]: <Axes: xlabel='BMI', ylabel='Glucose'>



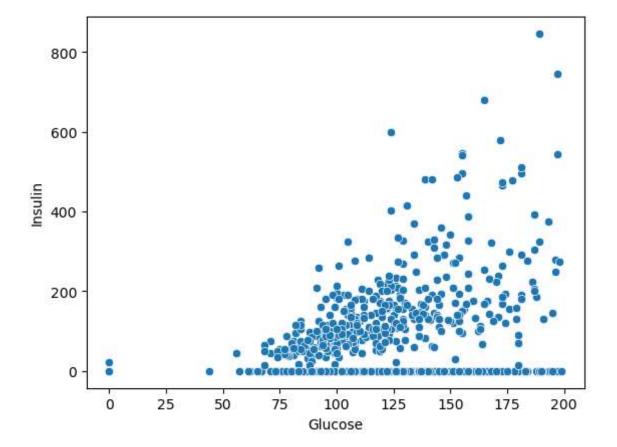
```
In [27]: sns.relplot(x='BMI', y= 'Glucose', data=df)
```

Out[27]: <seaborn.axisgrid.FacetGrid at 0x28b652c1ea0>



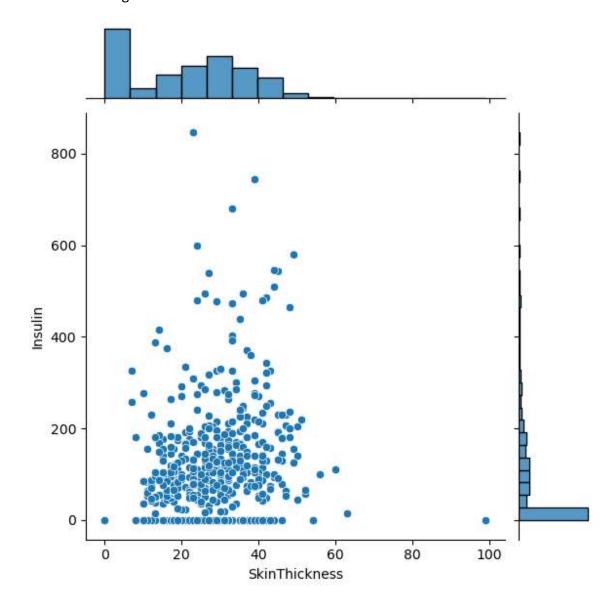
```
In [28]: sns.scatterplot(x='Glucose', y= 'Insulin', data=df)
```

Out[28]: <Axes: xlabel='Glucose', ylabel='Insulin'>



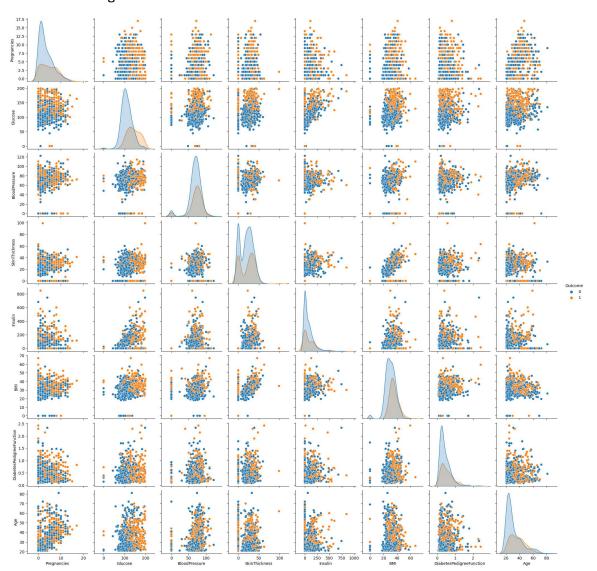
In [29]: sns.jointplot(x='SkinThickness', y= 'Insulin', data=df)

Out[29]: <seaborn.axisgrid.JointGrid at 0x28b6547a9e0>



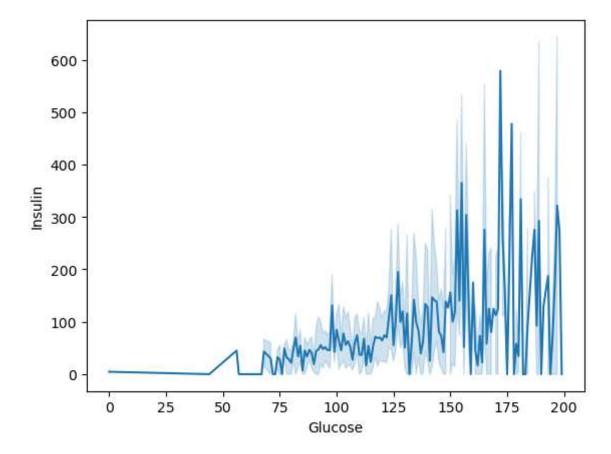
In [30]: sns.pairplot(df,hue='Outcome')

Out[30]: <seaborn.axisgrid.PairGrid at 0x28b654f6ce0>



```
In [31]: sns.lineplot(x='Glucose', y= 'Insulin', data=df)
```

Out[31]: <Axes: xlabel='Glucose', ylabel='Insulin'>



In [32]: sns.swarmplot(x='Glucose', y= 'Insulin', data=df)

c:\users\asnuk\anaconuas\iiv\site-packages\seavorn\categoricai.py:3544. UserWarning: 40.0% of the points cannot be placed; you may want to decrease the size of the markers or use stripplot.

warnings.warn(msg, UserWarning)

C:\Users\ashuk\anaconda3\lib\site-packages\seaborn\categorical.py:3544: U
serWarning: 80.0% of the points cannot be placed; you may want to decreas
e the size of the markers or use stripplot.

warnings.warn(msg, UserWarning)

C:\Users\ashuk\anaconda3\lib\site-packages\seaborn\categorical.py:3544: U serWarning: 16.7% of the points cannot be placed; you may want to decreas e the size of the markers or use stripplot.

warnings.warn(msg, UserWarning)

C:\Users\ashuk\anaconda3\lib\site-packages\seaborn\categorical.py:3544: U
serWarning: 62.5% of the points cannot be placed; you may want to decreas
e the size of the markers or use stripplot.

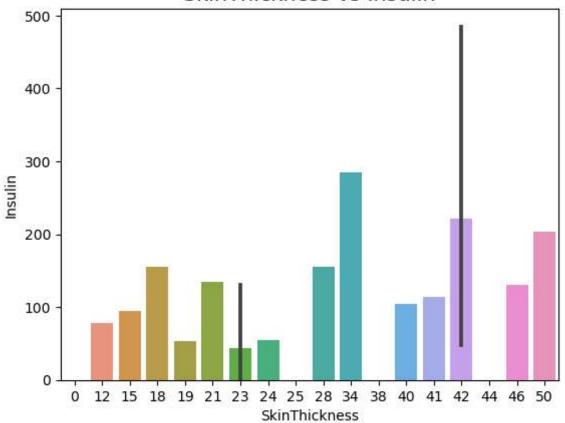
warnings.warn(msg, UserWarning)

C:\Users\ashuk\anaconda3\lib\site-packages\seaborn\categorical.py:3544: U serWarning: 20.0% of the points cannot be placed; you may want to decreas e the size of the markers or use stripplot.

warnings.warn(msg, UserWarning)

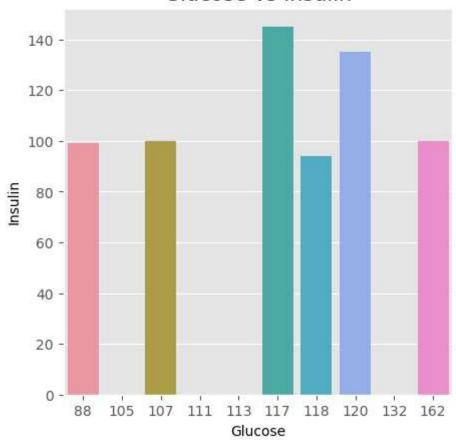
```
In [33]: sns.barplot(x="SkinThickness", y="Insulin", data=df[150:180])
    plt.title("SkinThickness vs Insulin",fontsize=15)
    plt.xlabel("SkinThickness")
    plt.ylabel("Insulin")
    plt.show()
    plt.style.use("ggplot")
```

SkinThickness vs Insulin



```
In [34]: plt.figure(figsize=(5,5))
    sns.barplot(x="Glucose", y="Insulin", data=df[120:130])
    plt.title("Glucose vs Insulin",fontsize=15)
    plt.xlabel("Glucose")
    plt.ylabel("Insulin")
    plt.show()
```

Glucose vs Insulin



```
In [37]: x = df.drop(columns = 'Outcome')
y = df['Outcome']
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_st
```

```
from sklearn.linear model import LogisticRegression
In [42]:
         model = LogisticRegression()
         model.fit(X train, y train)
         y pred = model.predict(X test)
         C:\Users\ashuk\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.p
         y:460: ConvergenceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html (https://sci
         kit-learn.org/stable/modules/preprocessing.html)
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regr
         ession (https://scikit-learn.org/stable/modules/linear_model.html#logistic-
         regression)
           n_iter_i = _check_optimize_result(
In [43]: | from sklearn.metrics import classification report
         from sklearn.metrics import confusion matrix
In [44]: | print(classification_report(y_test, y_pred))
         print(confusion matrix(y test, y pred))
         from sklearn.metrics import accuracy_score
         LRAcc = accuracy_score(y_pred,y_test)
         print('Logistic Regression accuracy is: {:.2f}%'.format(LRAcc*100))
                       precision
                                     recall f1-score
                                                        support
                    0
                            0.84
                                      0.92
                                                 0.88
                                                            107
                    1
                            0.76
                                      0.62
                                                 0.68
                                                             47
             accuracy
                                                 0.82
                                                            154
                            0.80
                                      0.77
                                                 0.78
                                                            154
            macro avg
         weighted avg
                            0.82
                                      0.82
                                                 0.82
                                                            154
         [[98 9]
```

[18 29]]

Logistic Regression accuracy is: 82.47%

```
In [45]:
        from sklearn.neighbors import KNeighborsClassifier
         model = KNeighborsClassifier(n_neighbors=7)
         model.fit(X_train, y_train)
         y_pred = model.predict(X_test)
         print(classification_report(y_test, y_pred))
         print(confusion_matrix(y_test, y_pred))
         from sklearn.metrics import accuracy_score
         KNAcc = accuracy_score(y_pred,y_test)
         print('KNeighborsClassifier accuracy is: {:.2f}%'.format(KNAcc*100))
                       precision
                                    recall f1-score
                                                        support
                    0
                            0.82
                                      0.84
                                                 0.83
                                                            107
                    1
                            0.61
                                      0.57
                                                0.59
                                                             47
                                                0.76
                                                            154
             accuracy
            macro avg
                            0.72
                                      0.71
                                                0.71
                                                            154
```

0.76

0.76

154

[[90 17] [20 27]]

weighted avg

KNeighborsClassifier accuracy is: 75.97%

0.76

```
In [46]: from sklearn.svm import SVC
    model = SVC()
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print(classification_report(y_test, y_pred))
    print(confusion_matrix(y_test, y_pred))
    from sklearn.metrics import accuracy_score
    SVCAcc = accuracy_score(y_pred,y_test)
    print('SVC accuracy is: {:.2f}%'.format(SVCAcc*100))
```

	precision	recall	f1-score	support
0	0.81	0.92	0.86	107
1	0.73	0.51	0.60	47
accuracy			0.79	154
macro avg	0.77	0.71	0.73	1 54
weighted avg	0.78	0.79	0.78	154

[[98 9] [23 24]]

SVC accuracy is: 79.22%

```
from sklearn.ensemble import RandomForestClassifier
In [47]:
         model = RandomForestClassifier()
         model.fit(X_train, y_train)
         y pred = model.predict(X test)
         print(classification_report(y_test, y_pred))
         print(confusion_matrix(y_test, y_pred))
                                     recall f1-score
                       precision
                                                        support
                    0
                             0.84
                                       0.87
                                                 0.85
                                                            107
                    1
                             0.67
                                       0.62
                                                 0.64
                                                             47
                                                            154
             accuracy
                                                 0.79
                            0.76
                                       0.74
                                                 0.75
                                                            154
            macro avg
                            0.79
                                       0.79
                                                 0.79
                                                            154
         weighted avg
         [[93 14]
          [18 29]]
In [48]: | from sklearn.metrics import accuracy_score
         RFAcc = accuracy score(y pred,y test)
         print('RFC accuracy is: {:.2f}%'.format(RFAcc*100))
         RFC accuracy is: 79.22%
In [49]: from sklearn.ensemble import GradientBoostingClassifier
         model = GradientBoostingClassifier()
         model.fit(X_train, y_train)
         y_pred = model.predict(X_test)
         print(classification_report(y_test, y_pred))
         print(confusion_matrix(y_test, y_pred))
         from sklearn.metrics import accuracy_score
         GBCAcc = accuracy_score(y_pred,y_test)
         print('GBC accuracy is: {:.2f}%'.format(GBCAcc*100))
                                     recall f1-score
                       precision
                                                        support
                    0
                                       0.86
                             0.86
                                                 0.86
                                                            107
                    1
                             0.68
                                       0.68
                                                 0.68
                                                             47
                                                 0.81
                                                            154
             accuracy
                            0.77
                                       0.77
            macro avg
                                                 0.77
                                                            154
                                       0.81
                                                 0.81
                                                            154
         weighted avg
                            0.81
```

[[92 15] [15 32]]

GBC accuracy is: 80.52%

```
In [50]: from sklearn.naive_bayes import GaussianNB
model = GaussianNB()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
from sklearn.metrics import accuracy_score
GNBAcc = accuracy_score(y_pred,y_test)
print('GNB accuracy is: {:.2f}%'.format(GNBAcc*100))
```

	precision	recall	f1-score	support
0 1	0.84 0.67	0.87 0.62	0.85 0.64	107 47
accuracy macro avg weighted avg	0.76 0.79	0.74 0.79	0.79 0.75 0.79	154 154 154

[[93 14] [18 29]] GNB accuracy is: 79.22%

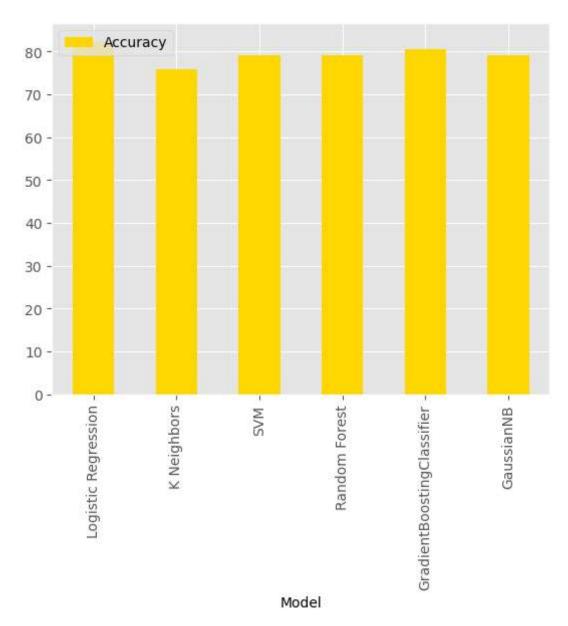
In [52]: compare = pd.DataFrame({'Model': ['Logistic Regression', 'K Neighbors', 'SVM
 'Accuracy': [LRAcc*100, KNAcc*100, SVCAcc*100, RFAcc*100, GBCAcc*100, GNBAcc*
 compare.sort_values(by='Accuracy', ascending=False)

Out[52]:

	Model	Accuracy
0	Logistic Regression	82.467532
4	GradientBoostingClassifier	80.519481
2	SVM	79.220779
3	Random Forest	79.220779
5	GaussianNB	79.220779
1	K Neighbors	75.974026

```
In [54]: compare.plot(x='Model', y='Accuracy', kind='bar', color='gold')
```

Out[54]: <Axes: xlabel='Model'>



```
In [ ]:
```