In [1]:

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

data = pd.read_csv('diabetes.csv')
data
```

Out[1]:

	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
...	...	...	...	...	...	...	...	...	...
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

768 rows × 9 columns

In [2]:

```
def print_vals(df, column_name):
    print("Mean: {:.3f}, Median: {:.3f}, Sample Std: {:.3f}, Pop. Std: {:.3f}, Sample Va
r: {:.3f}, Pop. Var: {:.3f}, Range: {:.3f}".
                                                  format(df[column_name].mean(), df[colum
n_name].median(),
                                                         df[column_name].std(), np.std(df
[column_name]), df[column_name].var(),
                                                         np.var(df[column_name]), df[colu
mn_name].max() - df[column_name].min()))
```

In [3]:

```
print_vals(data, 'Pregnancies')
```

```
Mean: 3.845, Median: 3.000, Sample Std: 3.370, Pop. Std: 3.367, Sample Var: 11.354, Pop.
Var: 11.339, Range: 17.000
```

In [4]:

```
print_vals(data, 'Glucose')
```

```
Mean: 120.895, Median: 117.000, Sample Std: 31.973, Pop. Std: 31.952, Sample Var: 1022.24
8, Pop. Var: 1020.917, Range: 199.000
```

In [5]:

```
print_vals(data, 'Insulin')
```

```
Mean: 79.799, Median: 30.500, Sample Std: 115.244, Pop. Std: 115.169, Sample Var: 13281.1
80, Pop. Var: 13263.887, Range: 846.000
```

In [6]:

```
print_vals(data, 'BloodPressure')
```

```
print_vals(data, 'BloodPressure')
```

```
Mean: 69.105, Median: 72.000, Sample Std: 19.356, Pop. Std: 19.343, Sample Var: 374.647,
Pop. Var: 374.159, Range: 122.000
```

In [7]:

```
print_vals(data, 'SkinThickness')
```

```
Mean: 20.536, Median: 23.000, Sample Std: 15.952, Pop. Std: 15.942, Sample Var: 254.473,
Pop. Var: 254.142, Range: 99.000
```

In [8]:

```
print_vals(data, 'BMI')
```

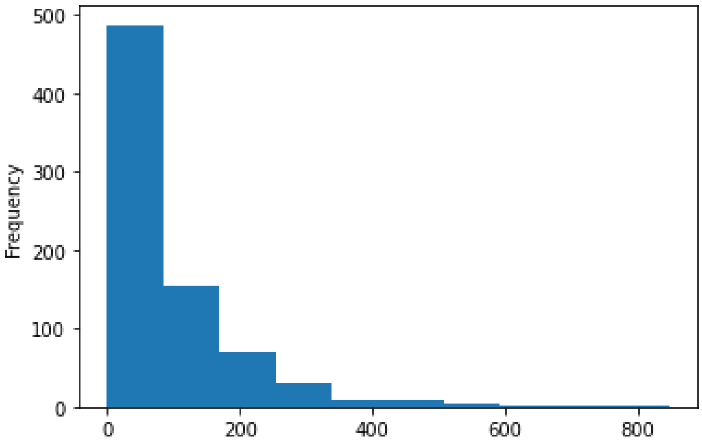
```
Mean: 31.993, Median: 32.000, Sample Std: 7.884, Pop. Std: 7.879, Sample Var: 62.160, Pop
. Var: 62.079, Range: 67.100
```

In [9]:

```
data['Insulin'].plot.hist()
```

Out[9]:

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

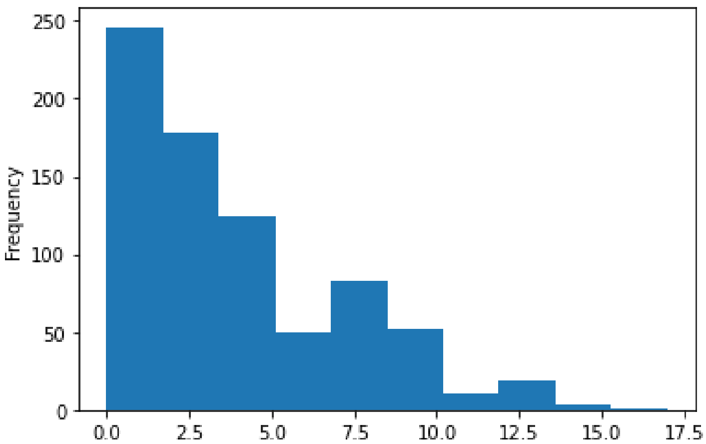


In [10]:

```
data['Pregnancies'].plot.hist()
```

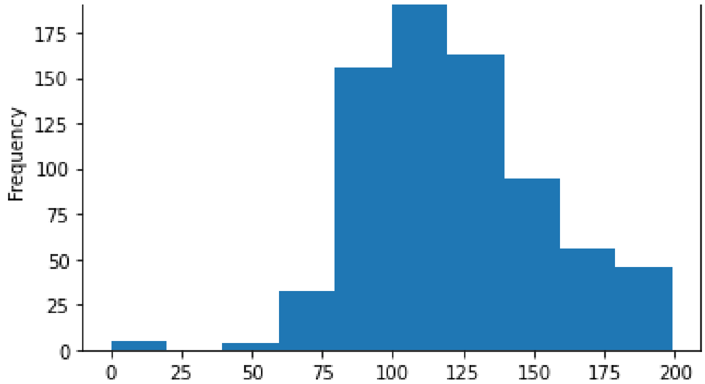
Out[10]:

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



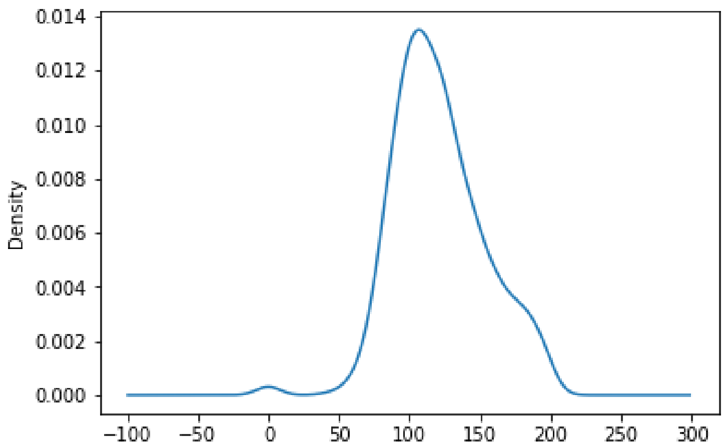
In [11]:

```
data['Glucose'].plot.hist()
plt.savefig('Glucose Histogram.png')
```



In [12]:

```
data['Glucose'].plot.kde()
plt.savefig('Glucose Density Graph.png')
```

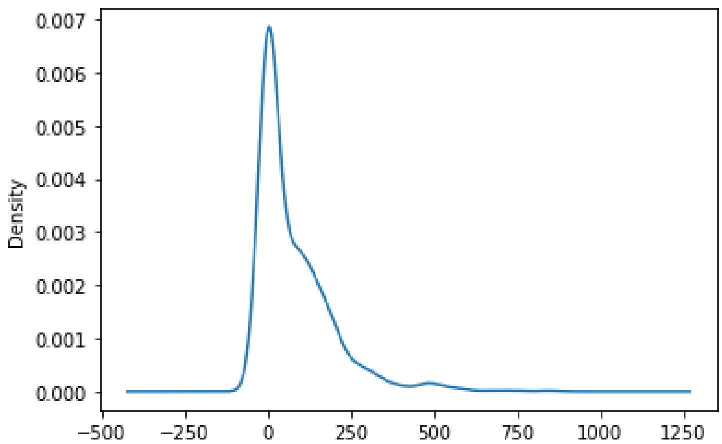


In [13]:

```
data['Insulin'].plot.kde()
```

Out[13]:

<AxesSubplot:ylabel='Density'>

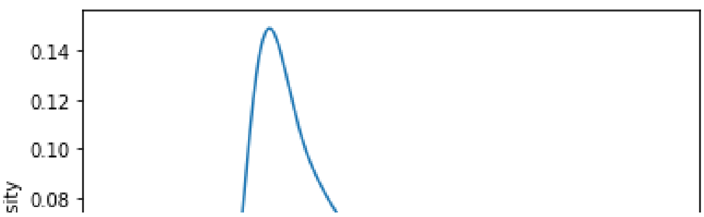


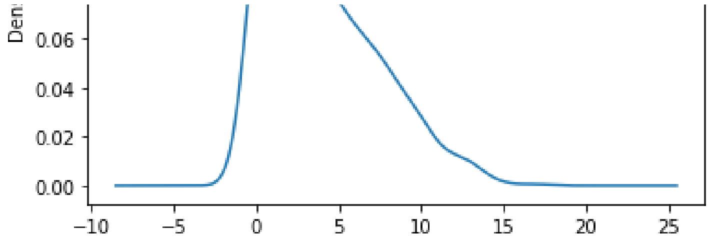
In [14]:

```
data['Pregnancies'].plot.kde()
```

Out[14]:

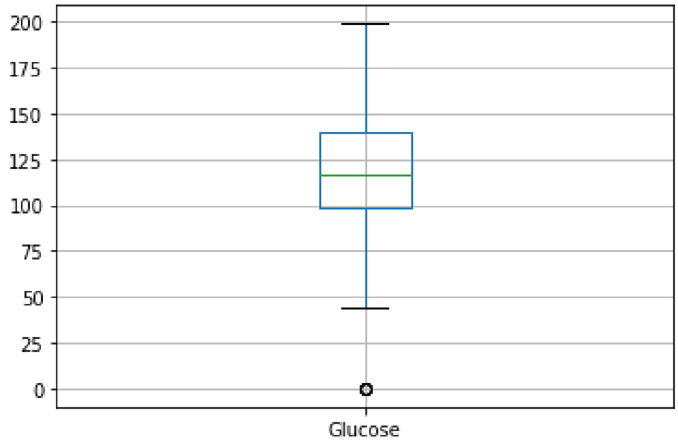
<AxesSubplot:ylabel='Density'>





In [15]:

```
data.boxplot(column=['Glucose'])
plt.savefig('Glucose Boxplot.png')
```

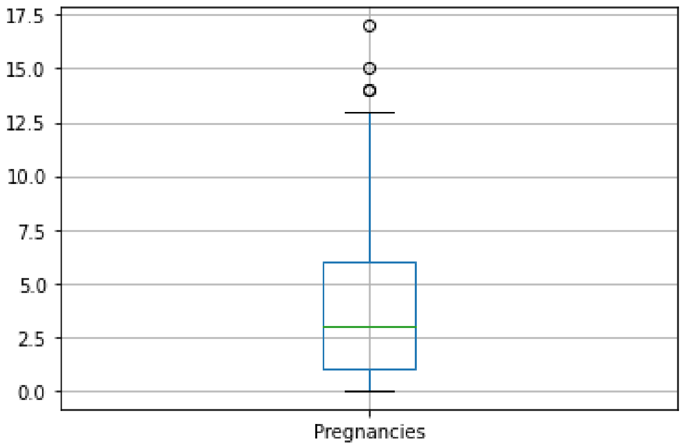


In [16]:

```
data.boxplot(column=['Pregnancies'])
```

Out[16]:

```
<AxesSubplot:>
```

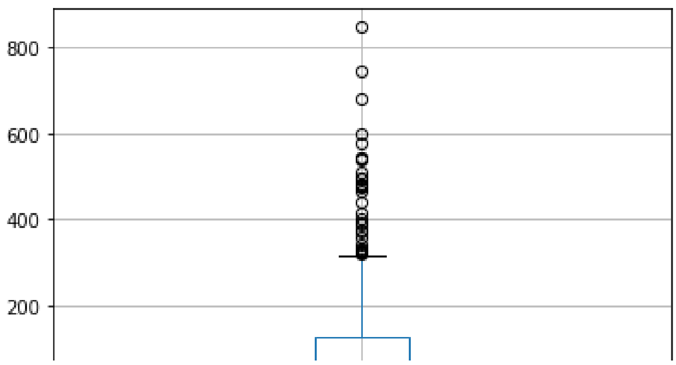


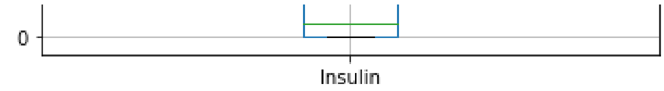
In [17]:

```
data.boxplot(column=['Insulin'])
```

Out[17]:

```
<AxesSubplot:>
```





In [18]:

```
def construct_reduced_pop(df, column):
    return pd.DataFrame([df[column].min(), df[column].max(), df[column].median(), df[col
umn].mean(), df[column].quantile(.25),
                         df[column].quantile(.75), df[column].quantile(.15), df[column].q
uantile(.85)])
```

In [19]:

```
reduced_pop = construct_reduced_pop(data, 'Glucose')
reduced_pop
```

Out[19]:

	0
0	0.000000
1	199.000000
2	117.000000
3	120.894531
4	99.000000
5	140.250000
6	91.000000
7	156.000000

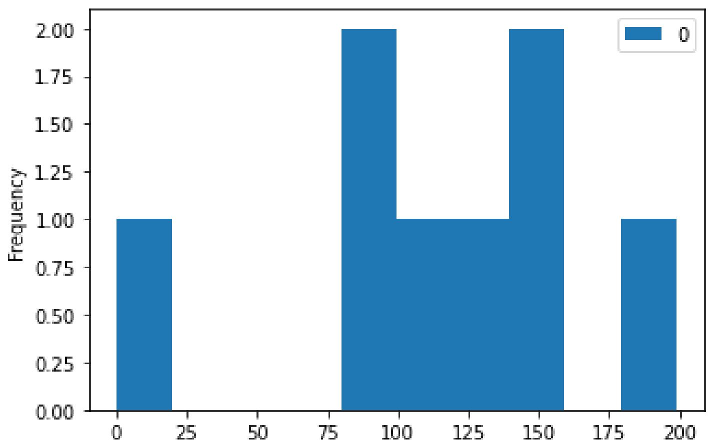
In [20]:

```
print_vals(reduced_pop, 0)
```

```
Mean: 115.393, Median: 118.947, Sample Std: 57.903, Pop. Std: 54.163, Sample Var: 3352.72
5, Pop. Var: 2933.634, Range: 199.000
```

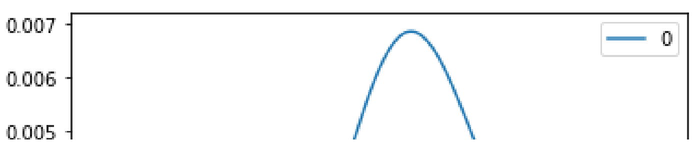
In [21]:

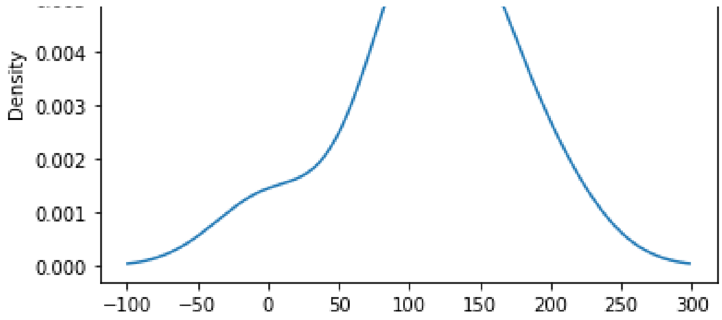
```
reduced_pop.plot.hist()
plt.savefig('Reduced Pop Histogram.png')
```



In [22]:

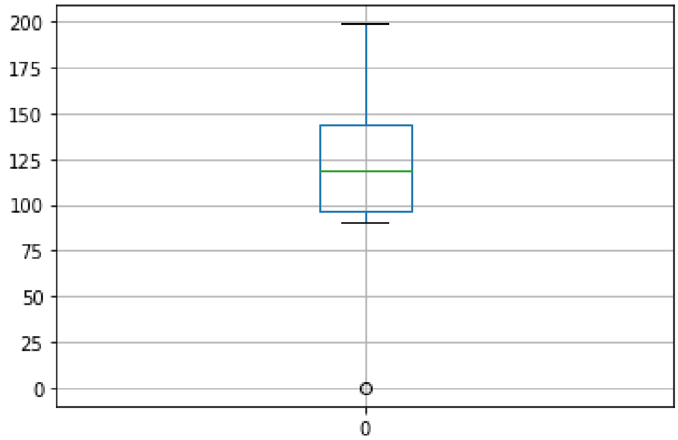
```
reduced_pop.plot.kde()
plt.savefig('Reduced Pop Density.png')
```





In [23]:

```
reduced_pop.boxplot()
plt.savefig('Reduced Pop Boxplot.png')
```



In [24]:

```
reduced_pop.mean()[0]
```

Out[24]:

```
115.39306640625
```

In [25]:

```
reduced_pop.var()[0]
```

Out[25]:

```
3352.7245698656357
```

In [26]:

```
np.var(reduced_pop)[0]
```

Out[26]:

```
2933.633998632431
```

In [27]:

```
from itertools import combinations

def sampling_dist_sample_mean(df, size, n=3):
    # Get all possible combinations of indices of array for samples (size choose n (8 cho
ose 3))
    combos = combinations(range(size), n)
    means = []
    var = []
    dist = []

    # Calculations on each sample
    for c in combos:
        means.append(df.iloc[list(c)].mean()[0])
        var.append(df.iloc[list(c)].var()[0])
```

```
            dist.append(np.array(df.iloc[list(c)]))
            #print(df.iloc[list(c)])
            #print(df.iloc[list(c)].mean())
    #print(len(list(combos)))
    return means, dist, var
```

In [28]:

```
means, dist, var = sampling_dist_sample_mean(reduced_pop, 8, 3)
```

In [29]:

```
np.mean(means)
```

Out[29]:

```
115.39306640625
```

In [30]:

```
np.var(means)
```

Out[30]:

```
698.484285388674
```

In [31]:

```
pd.DataFrame(means).var()
```

Out[31]:

```
0    711.184
dtype: float64
```

In [32]:

```
np.mean(var)
```

Out[32]:

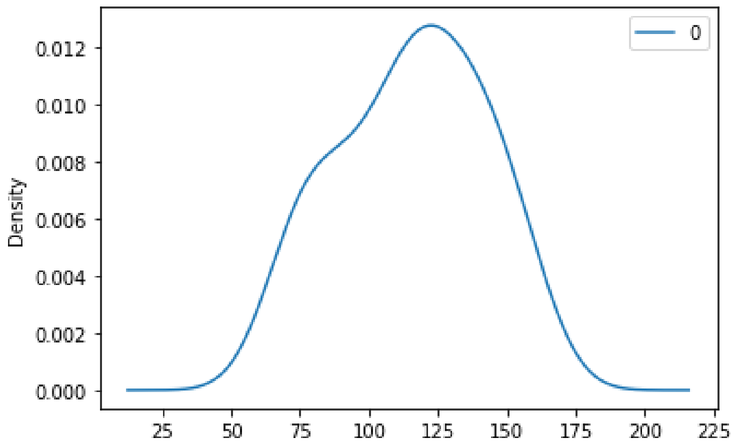
```
3352.7245698656347
```

In [33]:

```
pd.DataFrame(means).plot.kde()
```

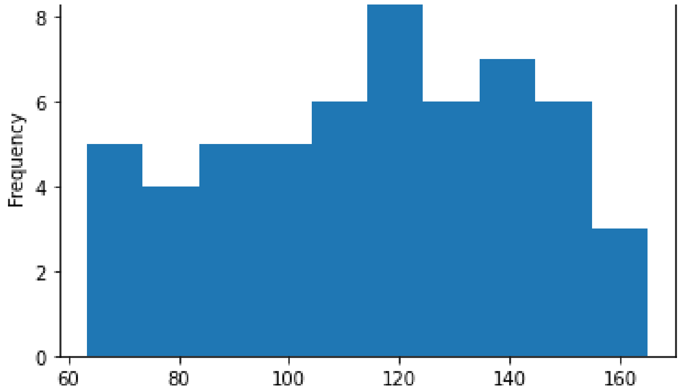
Out[33]:

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



In [34]:

```
pd.DataFrame(means).plot.hist()
plt.savefig('Sampling Dist of Sample Mean.png')
```



In [35]:

```
def var_single_sample(n, N, sample):
    s_squared = pd.DataFrame(sample).var()[0]
    print("s^2: {:.2f}".format(s_squared))
    return (1 - (n/N)) * (s_squared / n)
```

In [36]:

```
dist[5]
```

Out[36]:

```
array([[  0.],
       [199.],
       [156.]])
```

In [37]:

```
var_single_sample(3, 8, dist[5])
```

```
s^2: 10964.33
```

Out[37]:

```
2284.2361111111113
```

In [38]:

```
var_single_sample(3, 8, dist[10])
```

```
s^2: 6591.00
```

Out[38]:

```
1373.125
```

In [39]:

```
var_single_sample(3, 8, dist[30])
```

```
s^2: 2525.52
```

Out[39]:

```
526.1501736111111
```

In [40]:

```
var_single_sample(3, 8, dist[25])
```

```
s^2: 1682.33
```

Out[40]:

```
350.4861111111111
```

In [41]:

```
(var_single_sample(3, 8, dist[5]) + var_single_sample(3, 8, dist[10]) + var_single_sampl
```

```
e(3, 8, dist[30])) / 3
```

```
s^2: 10964.33
s^2: 6591.00
s^2: 2525.52
```

Out[41]:

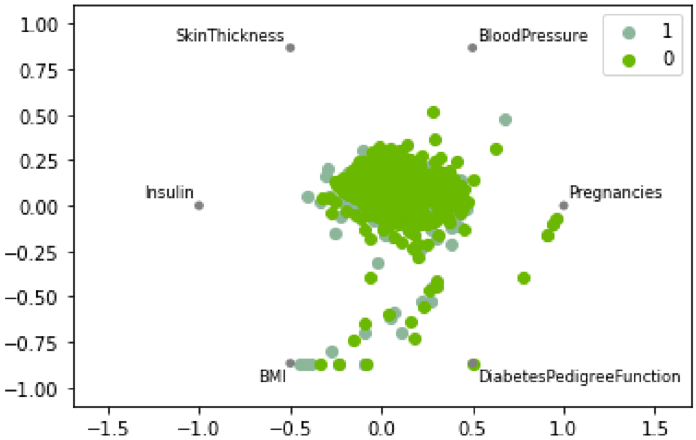
```
1394.5037615740741
```

In [42]:

```
pd.plotting.radviz(data.iloc[:, [0,2,3,4,5,6,8]], 'Outcome')
```

Out[42]:

```
<AxesSubplot:>
```



In [49]:

```
from datetime import datetime
import time

# Import classifiers
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC

# Import metrics
from sklearn.metrics import precision_score, balanced_accuracy_score, accuracy_score, rec
all_score, f1_score, classification_report, roc_auc_score, confusion_matrix, roc_curve, a
uc, precision_recall_fscore_support, average_precision_score, make_scorer

# Import data preprocessing libraries
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split


# Define models
lr = LogisticRegression(random_state=0)
knn = KNeighborsClassifier(n_neighbors=10, metric='minkowski', p=10)
nb = GaussianNB()
svc = SVC(kernel='linear', random_state=0, probability=True)
rf = RandomForestClassifier(random_state=0)
dt = DecisionTreeClassifier(random_state=0)

# Create list of models
models = []
models.append(('Logistic Regression', lr))
models.append(('KNN', knn))
models.append(('Naive Bayes', nb))
models.append(('SVC', svc))
models.append(('Decision Tree', dt))
```

```python
models.append(('Random Forest', rf))

# Empirical evaluation of all models: cross validation and test set accuray
def run_models(X, y, test_size=1/5):
    print('Running models...')
    sc = StandardScaler()
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size, rando
m_state=0, stratify=y)
    X_train = sc.fit_transform(X_train)
    X_test = sc.transform(X_test)

    for name, model in models:
        model.fit(X_train, y_train)
        accuracy = model.score(X_test, y_test)

        print(name, 'Accuracy:', accuracy)
        y_pred = model.predict(X_test)

        #print('AUC:', get_auc(y_test, y_pred))
        print('Average precision:', average_precision_score(y_test, y_pred))
        print('Precision:', precision_score(y_test, y_pred))
        print('Recall:', recall_score(y_test, y_pred))
        print('F1 Score:', f1_score(y_test, y_pred))
        print('Confusion Matrix')
        print(confusion_matrix(y_test, y_pred))
        print()
```

In [50]:

```python
data.iloc[:, [0,1,3,4,5,6]]
```

Out[50]:

	Pregnancies	Glucose	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction
0	6	148	35	0	33.6	0.627
1	1	85	29	0	26.6	0.351
2	8	183	0	0	23.3	0.672
3	1	89	23	94	28.1	0.167
4	0	137	35	168	43.1	2.288
...	...	...	...	...	...	...
763	10	101	48	180	32.9	0.171
764	2	122	27	0	36.8	0.340
765	5	121	23	112	26.2	0.245
766	1	126	0	0	30.1	0.349
767	1	93	31	0	30.4	0.315

768 rows × 6 columns

In [51]:

```python
run_models(data.iloc[:, [1,3,4,5,6]], data.iloc[:, -1], test_size=.2)
```

```
Running models...
Logistic Regression Accuracy: 0.8116883116883117
Average precision: 0.6277168137633253
Precision: 0.7906976744186046
Recall: 0.6296296296296297
F1 Score: 0.7010309278350516
Confusion Matrix
[[91  9]
 [20 34]]

KNN Accuracy: 0.7857142857142857
Average precision: 0.5831945831945833
Precision: 0.7692307692307693
```

```
Precision: 0.7692307692307693
Recall: 0.5555555555555556
F1 Score: 0.6451612903225806
Confusion Matrix
[[91  9]
 [24 30]]

Naive Bayes Accuracy: 0.7597402597402597
Average precision: 0.5463244399414612
Precision: 0.6808510638297872
Recall: 0.5925925925925926
F1 Score: 0.6336633663366336
Confusion Matrix
[[85 15]
 [22 32]]

SVC Accuracy: 0.7987012987012987
Average precision: 0.6053684346367273
Precision: 0.7804878048780488
Recall: 0.5925925925925926
F1 Score: 0.6736842105263158
Confusion Matrix
[[91  9]
 [22 32]]

Decision Tree Accuracy: 0.7532467532467533
Average precision: 0.5379188712522046
Precision: 0.6666666666666666
Recall: 0.5925925925925926
F1 Score: 0.627450980392157
Confusion Matrix
[[84 16]
 [22 32]]

Random Forest Accuracy: 0.7857142857142857
Average precision: 0.5853468832192237
Precision: 0.723404255319149
Recall: 0.6296296296296297
F1 Score: 0.6732673267326733
Confusion Matrix
[[87 13]
 [20 34]]
```

In [ ]: