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In [25]:
```
# Importing Libraries

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
import warnings
from sklearn.metrics import classification_report,ConfusionMatrixDisplay
warnings.filterwarnings('ignore')
```

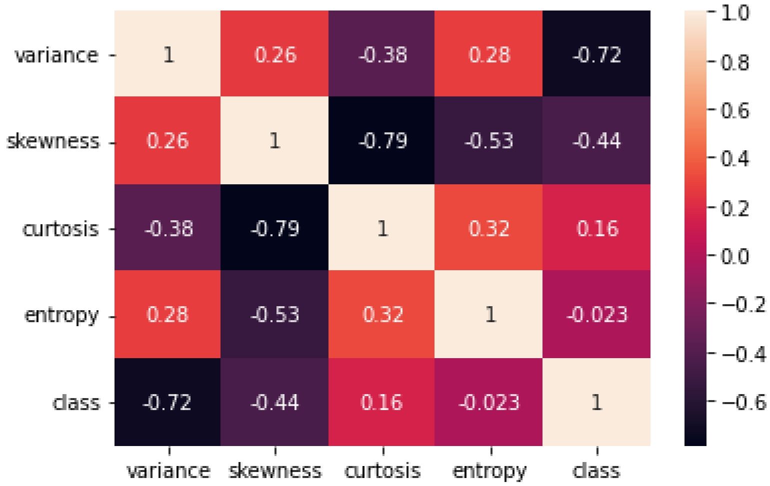
In [3]:
```
# Reading dataset

dataset = pd.read_csv('bank.csv')
dataset
```

Out[3]:

	variance	skewness	curtosis	entropy	class
0	3.62160	8.66610	-2.8073	-0.44699	0
1	4.54590	8.16740	-2.4586	-1.46210	0
2	3.86600	-2.63830	1.9242	0.10645	0
3	3.45660	9.52280	-4.0112	-3.59440	0
4	0.32924	-4.45520	4.5718	-0.98880	0
...	...	...	...	...	...
1367	0.40614	1.34920	-1.4501	-0.55949	1
1368	-1.38870	-4.87730	6.4774	0.34179	1
1369	-3.75030	-13.45860	17.5932	-2.77710	1
1370	-3.56370	-8.38270	12.3930	-1.28230	1
1371	-2.54190	-0.65804	2.6842	1.19520	1

1372 rows × 5 columns

In [4]:
```
# Correlation Matrix

correl = dataset.corr()
sns.heatmap(correl,annot=True)
plt.show()
```



Hence important attributes to predict class are : variance, skewness and curtosis

In [5]:
```
X = dataset[['variance','skewness','curtosis']]
y = dataset['class']
X
```

Out[5]:

	variance	skewness	curtosis
0	3.62160	8.66610	-2.8073
1	4.54590	8.16740	-2.4586
2	3.86600	-2.63830	1.9242
3	3.45660	9.52280	-4.0112
4	0.32924	-4.45520	4.5718
...	...	...	...
1367	0.40614	1.34920	-1.4501
1368	-1.38870	-4.87730	6.4774
1369	-3.75030	-13.45860	17.5932
1370	-3.56370	-8.38270	12.3930
1371	-2.54190	-0.65804	2.6842

1372 rows × 3 columns

In [6]:
```
# Splitting data into training and test set

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,
                                                    random_state=13)
X_train
```

Out[6]:

	variance	skewness	curtosis
523	2.13190	-2.0403	2.55740
486	3.88320	6.4023	-2.43200
784	-3.40830	4.8587	-0.76888
408	4.22300	1.1319	0.72202
1318	-0.49281	3.0605	-1.83560

	variance	skewness	curtosis
...	...	...	...
866	-4.14090	3.4619	-0.47841
742	0.66191	9.6594	-0.28819
74	4.40690	10.9072	-4.57750
176	0.19081	9.1297	-3.72500
338	0.96414	5.6160	2.21380

960 rows × 3 columns

In [9]:

```
# Standardization

sc = StandardScaler()
X_train[['variance','skewness','curtosis']] =  sc.fit_transform(X_train)
X_test[['variance','skewness','curtosis']]  = sc.transform(X_test)
X_train
```

Out[9]:

	variance	skewness	curtosis
523	0.575079	-0.705603	0.309801
486	1.190045	0.760590	-0.881646
784	-1.370354	0.492519	-0.484500
408	1.309365	-0.154700	-0.128480
1318	-0.346584	0.180233	-0.739228
...	...	...	...
866	-1.627606	0.249942	-0.415137
742	0.058894	1.326238	-0.369714
74	1.373941	1.542939	-1.393981
176	-0.106532	1.234247	-1.190408
338	0.165021	0.624037	0.227750

960 rows × 3 columns

In [10]:

```
X_test
```

Out[10]:

	variance	skewness	curtosis
308	1.447367	1.416440	-1.308254
1330	-0.559974	-1.610491	1.135197
472	1.174314	0.722870	-0.788969
304	0.659705	1.467464	-1.019359
33	-0.512432	1.283117	0.112341
...	...	...	...
1174	-1.299001	-0.376070	-0.067914

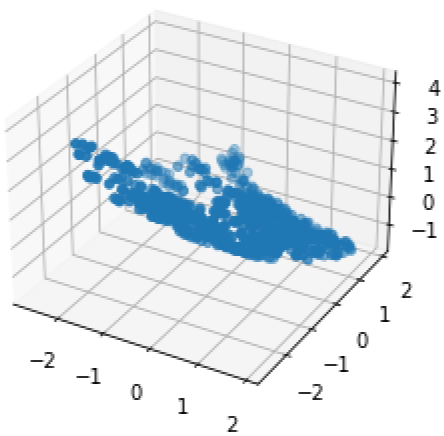
	variance	skewness	curtosis
642	1.628594	-0.356664	-0.223010
883	-1.353534	-0.408054	0.208312
1319	0.059505	-0.359180	-0.345774
298	0.227828	-0.206450	1.001782

412 rows × 3 columns

In [11]:

```
# 3D plot of features

fig = plt.figure()
ax = plt.axes(projection ='3d')

ax.scatter(X_train['variance'],X_train['skewness'],X_train['curtosis'])
ax.set_title('3D plot of Training set')
plt.show()
```

3D plot of Training set



Principal Component Analysis

In [12]:

```
# PCA

pca = PCA(n_components=2)
X_train_2dim = pd.DataFrame(pca.fit_transform(X_train),
                            columns = [['prin_comp1',
                                        'prin_comp2']])

X_test_2dim = pd.DataFrame(pca.transform(X_test),
                           columns = [['prin_comp1',
                                       'prin_comp2']])

X_train_1dim = X_train_2dim['prin_comp1']
X_test_1dim = X_test_2dim['prin_comp1']

X_train_2dim
```

Out[12]:

	prin_comp1	prin_comp2
0	0.410836	-0.850324
1	-1.550447	-0.606319

	prin_comp1	prin_comp2
2	-0.063089	1.521691
3	-0.527711	-1.214560
4	-0.456614	0.530071
...	...	...
955	0.241589	1.647311
956	-1.103047	0.527134
957	-2.456243	-0.370786
958	-1.516537	0.806281
959	-0.311519	0.043388

960 rows × 2 columns

In [13]:

```
X_train_1dim
```

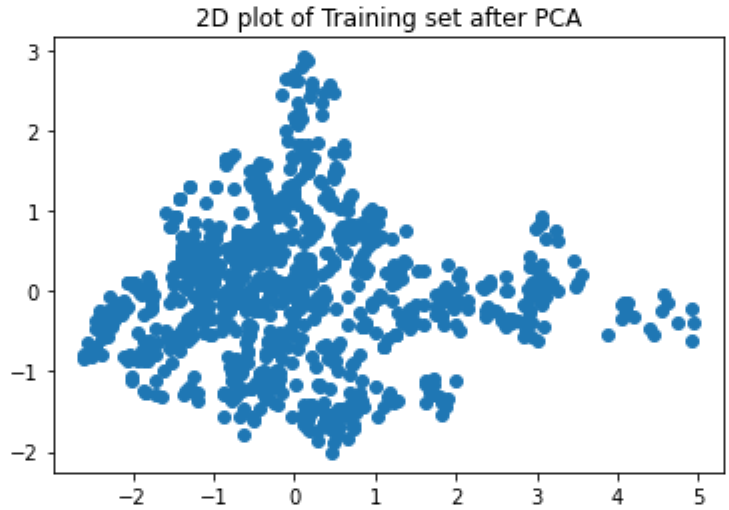
Out[13]:

	prin_comp1
0	0.410836
1	-1.550447
2	-0.063089
3	-0.527711
4	-0.456614
...	...
955	0.241589
956	-1.103047
957	-2.456243
958	-1.516537
959	-0.311519

960 rows × 1 columns

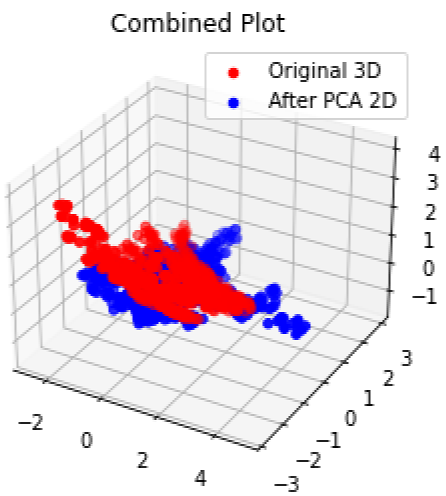
In [14]:

```
# 2D plot of features

plt.scatter(X_train_2dim['prin_comp1'],X_train_2dim['prin_comp2'])
plt.title('2D plot of Training set after PCA')
plt.show()
```



In [15]:

```
# Combined 3D and 2D plot of features

fig = plt.figure()
ax = plt.axes(projection ='3d')

ax.scatter(X_train['variance'],X_train['skewness'],X_train['curtosis'],color='red')
ax.scatter(X_train_2dim['prin_comp1'],X_train_2dim['prin_comp2'],color='blue')
ax.set_title('Combined Plot')
plt.legend(labels=['Original 3D','After PCA 2D'])
plt.show()
```



In [32]:

```
# PCA Info

print('Info retained by PCA components (%) : ',
      [val*100 for val in pca.explained_variance_ratio_])
print()
print('Eigen Values : ',
      pca.explained_variance_)
print()
print('Eigen Vectors : ')
print(pca.components_)
```

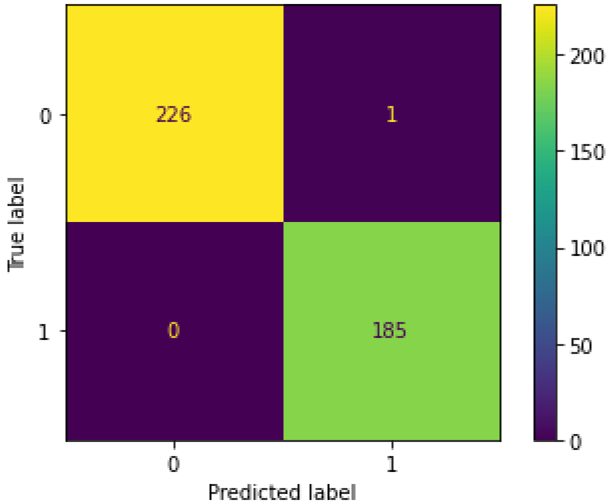
```
Info retained by PCA components (%) :  [66.02418112135348, 26.985386638430341]

Eigen Values :  [1.98279084 0.81040577]

Eigen Vectors :
[[-0.41293121 -0.63003301  0.65768246]
 [-0.90224817  0.38148952 -0.20103233]]
```

K Nearest Neighbors

In [26]:

```
# KNN On Original Dataset

knn = KNeighborsClassifier()
knn.fit(X_train,y_train)

print('Model performance on original training set : ')
print()
print(classification_report(y_train,
                            knn.predict(X_train)))

print()
print('Model performance on original test set : ')
print()
print(classification_report(y_test,
                            knn.predict(X_test)))
print()
print('Confusion Matrix : ')
cm_display = ConfusionMatrixDisplay.from_estimator(
             knn, X_test, y_test,
             display_labels=['0','1'])
plt.show()
```

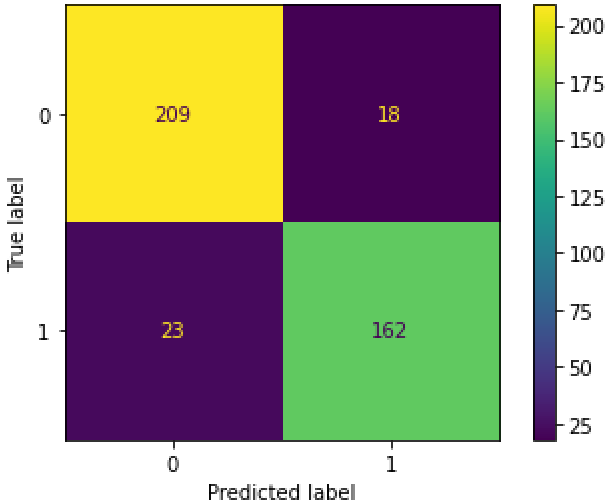
```
Model performance on original training set :

              precision    recall  f1-score   support

           0       1.00      1.00      1.00       535
           1       1.00      1.00      1.00       425

    accuracy                           1.00       960
   macro avg       1.00      1.00      1.00       960
weighted avg       1.00      1.00      1.00       960


Model performance on original test set :

              precision    recall  f1-score   support

           0       1.00      1.00      1.00       227
           1       0.99      1.00      1.00       185

    accuracy                           1.00       412
   macro avg       1.00      1.00      1.00       412
weighted avg       1.00      1.00      1.00       412


Confusion Matrix :
```



In [28]:

```
# KNN On 2D PCA

knn = KNeighborsClassifier()
knn.fit(X_train_2dim,y_train)

print('Model performance after 2D PCA on training set : ')
print()
print(classification_report(y_train,
                            knn.predict(X_train_2dim)))

print()
print('Model performance after 2D PCA on test set : ')
print()
print(classification_report(y_test,
                            knn.predict(X_test_2dim)))
print()
print('Confusion Matrix : ')
cm_display = ConfusionMatrixDisplay.from_estimator(
             knn, X_test_2dim, y_test,
             display_labels=['0','1'])
plt.show()
```

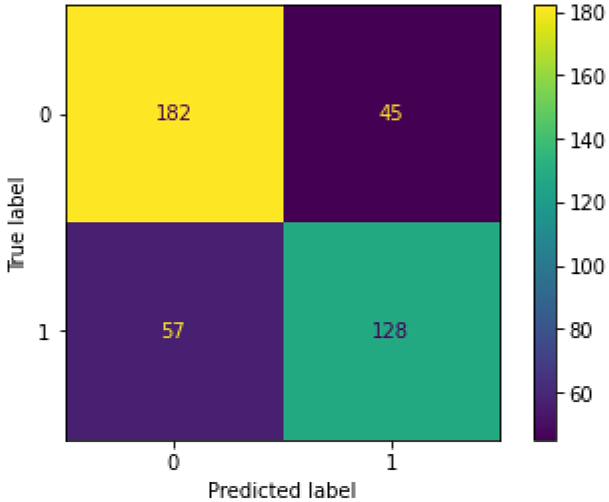
```
Model performance after 2D PCA on training set :

              precision    recall  f1-score   support

           0       0.95      0.94      0.95       535
           1       0.92      0.94      0.93       425

    accuracy                           0.94       960
   macro avg       0.94      0.94      0.94       960
weighted avg       0.94      0.94      0.94       960


Model performance after 2D PCA on test set :

              precision    recall  f1-score   support

           0       0.90      0.92      0.91       227
           1       0.90      0.88      0.89       185

    accuracy                           0.90       412
   macro avg       0.90      0.90      0.90       412
weighted avg       0.90      0.90      0.90       412


Confusion Matrix :
```



In [29]:

```python
# KNN On 1D PCA

knn = KNeighborsClassifier()
knn.fit(X_train_1dim,y_train)

print('Model performance after 1D PCA on training set : ')
print()
print(classification_report(y_train,
                            knn.predict(X_train_1dim)))

print()
print('Model performance after 1D PCA on test set : ')
print()
print(classification_report(y_test,
                            knn.predict(X_test_1dim)))
print()
print('Confusion Matrix : ')
cm_display = ConfusionMatrixDisplay.from_estimator(
             knn, X_test_1dim, y_test,
             display_labels=['0','1'])
plt.show()
```

```
Model performance after 1D PCA on training set :

              precision    recall  f1-score   support

           0       0.79      0.84      0.81       535
           1       0.78      0.71      0.74       425

    accuracy                           0.78       960
   macro avg       0.78      0.78      0.78       960
weighted avg       0.78      0.78      0.78       960


Model performance after 1D PCA on test set :

              precision    recall  f1-score   support

           0       0.76      0.80      0.78       227
           1       0.74      0.69      0.72       185

    accuracy                           0.75       412
   macro avg       0.75      0.75      0.75       412
weighted avg       0.75      0.75      0.75       412


Confusion Matrix :
```



Comparison of Results

In [31]:
```
result = pd.DataFrame({'Original':[100,100],
                       '2D PCA':[94,90],
                       '1D PCA':[78,75]},
                       index=['Training Accuracy (%)','Testing Accuracy (%)'])
print('Comparing Performance before and after PCA : \n')
result
```

```
Comparing Performance before and after PCA :
```

Out[31]:

	Original	2D PCA	1D PCA
Training Accuracy (%)	100	94	78
Testing Accuracy (%)	100	90	75

Conclusion : We can reduce dataset to 2 dimensions and still get a 94% accuracy on training set and 90% accuracy on test set hence reducing dataset to 2 dimensions using PCA would be a good choice