

# **Bank Note Analysis**

#### **Data Set Information:**

Data were extracted from images that were taken from genuine and forged banknote-like specimens. For digitization, an industrial camera usually used for print inspection was used. The final images have 400x 400 pixels. Due to the object lens and distance to the investigated object gray-scale pictures with a resolution of about 660 dpi were gained. Wavelet Transform tool were used to extract features from images.

#### **Attribute Information:**

- 1. variance of Wavelet Transformed image (continuous)
- 2. skewness of Wavelet Transformed image (continuous)
- 3. curtosis of Wavelet Transformed image (continuous)
- 4. entropy of image (continuous)
- 5. class (integer)

**Dataset:** <a href="https://www.kaggle.com/ritesaluja/bank-note-authentication-uci-data">https://www.kaggle.com/ritesaluja/bank-note-authentication-uci-data</a> (<a href="https://www.kaggle.com/ritesaluja/bank-note-authentication-uci-data">https://www.kaggle.com/ritesaluja/bank-note-authentication-uci-data</a> (<a href="https://www.kaggle.com/ritesaluja/bank-note-authentication-uci-data">https://www.kaggle.com/ritesaluja/bank-note-authentication-uci-data</a> (<a href="https://www.kaggle.com/ritesaluja/bank-note-authentication-uci-data">https://www.kaggle.com/ritesaluja/bank-note-authentication-uci-data">https://www.kaggle.com/ritesaluja/bank-note-authentication-uci-data</a> (<a href="https://www.kaggle.com/ritesaluja/bank-note-authentication-uci-data">https://www.kaggle.com/ritesaluja/bank-note-authentication-uci-data</a>)

**UCI:** <a href="http://archive.ics.uci.edu/ml/datasets/banknote+authentication">http://archive.ics.uci.edu/ml/datasets/banknote+authentication</a>)

# Can we classify banknote as fake or genuine?

In [65]: from pyforest import\*

```
In [66]: lazy_imports()
Out [66]: ['import os',
           'import plotly.express as px',
           'import altair as alt',
           'import plotly.graph_objs as go',
           'import keras',
           'import bokeh',
           'import datetime as dt',
           'from sklearn.preprocessing import OneHotEncoder',
           'from pathlib import Path',
           'import sklearn',
           'import numpy as np',
           'from sklearn.manifold import TSNE',
           'from sklearn.ensemble import GradientBoostingRegressor',
           'import re',
           'import plotly as py',
           'from sklearn.model_selection import train_test_split',
           'import statistics',
           'from sklearn.ensemble import RandomForestClassifier',
           'import nltk',
           'from sklearn.ensemble import RandomForestRegressor',
           'import tensorflow as tf',
           'from sklearn import svm',
           'import pickle',
           'import dash',
           'import matplotlib as mpl',
           'from dask import dataframe as dd',
           'from sklearn.feature_extraction.text import TfidfVectorizer',
           'import tqdm',
           'from pyspark import SparkContext',
           'from sklearn.ensemble import GradientBoostingClassifier',
           'import spacy',
           'import gensim',
           'import pydot',
           'from openpyxl import load_workbook',
           'import glob',
           'import sys']
In [67]:
          df=pd.read_csv('BankNote_Authentication.csv')
In [68]:
          df.head()
Out [68]:
             variance skewness curtosis entropy class
          0 3.62160
                       8.6661
                              -2.8073 -0.44699
             4.54590
                       8.1674
                              -2.4586 -1.46210
          2 3.86600
                      -2.6383
                              1.9242 0.10645
          3
             3.45660
                       9.5228
                              -4.0112 -3.59440
                                               0
          4 0.32924
                      -4.4552
                              4.5718 -0.98880
                                               O
In [69]:
          df.shape
Out[69]: (1372, 5)
         df['class'].value_counts()
Out[70]: 0
               762
          1
               610
         Name: class, dtype: int64
```

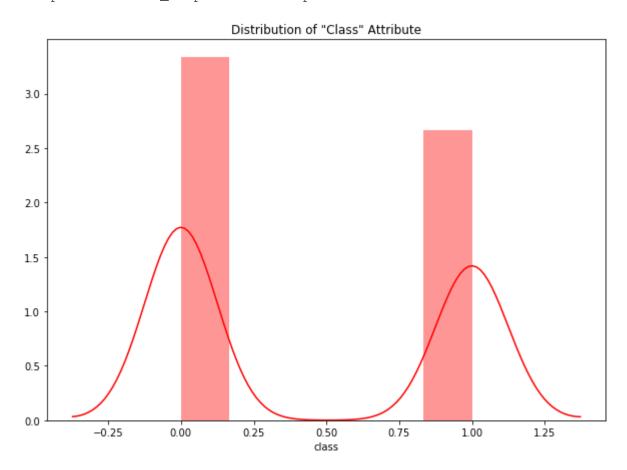
```
In [71]: df.isna().sum()
Out[71]: variance
         skewness
         curtosis
                      0
                      0
         entropy
         class
         dtype: int64
In [72]: df.dtypes
Out[72]: variance
                      float64
         skewness
                      float64
                      float64
         curtosis
         entropy
                      float64
                        int64
         class
         dtype: object
```

# **Visualizations**

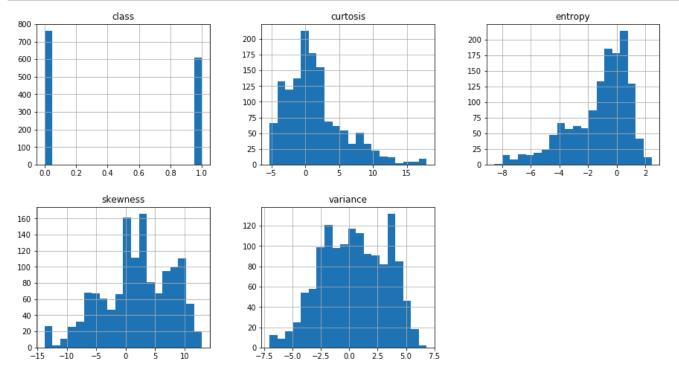
## **Univariate Data Analysis**

```
In [73]: plt.figure(figsize=(10,7))
    plt.title('Distribution of "Class" Attribute')
    sns.distplot(df['class'],color='red')
```

Out[73]: <matplotlib.axes.\_subplots.AxesSubplot at 0x125c39358>



```
In [74]: df.hist(bins=20, figsize=(15,8),layout=(2,3)); #Histogram of all the attributes
```



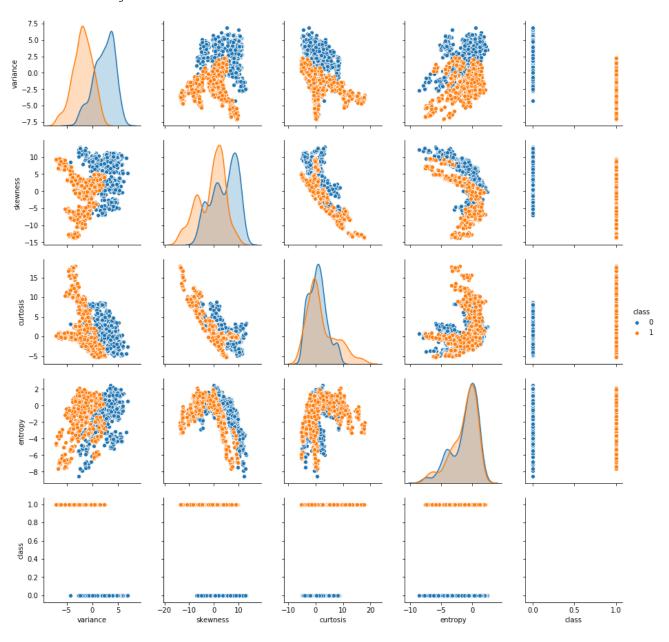
```
In [75]: # col_names = df.drop('class', axis = 1).columns.tolist()

# plt.figure(figsize = (10,3))
# i = 0
# for col in col_names:
# plt.subplot(1,4,i+1)
# plt.grid(True, alpha = 0.5)
# sns.kdeplot(df[col][df['class'] ==0], label = 'Fake note')
# sns.kdeplot(df[col][df['class'] ==1], label = 'Original note')
# plt.title('Class vs ' + col)
# plt.tight_layout()
# i+=1
# plt.show()
```

```
In [76]: import warnings
warnings.filterwarnings('ignore')
```

In [77]: sns.pairplot(df, hue="class")

Out[77]: <seaborn.axisgrid.PairGrid at 0x125e077b8>



# **Preparing Our Data To Build Our Model**

```
In [78]: df.head()
```

Out[78]:

	variance	skewness	curtosis	entropy	class
0	3.62160	8.6661	-2.8073	-0.44699	0
1	4.54590	8.1674	-2.4586	-1.46210	0
2	3.86600	-2.6383	1.9242	0.10645	0
3	3.45660	9.5228	-4.0112	-3.59440	0
4	0.32924	-4.4552	4.5718	-0.98880	0

```
In [79]: #defining features and target variable
X = df.drop(['class'], axis=1)
y = df['class']
```

```
In [80]: from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, rando m_state=1)
```

#### **Scaling Our Data**

Name: class, dtype: int64

```
In [81]: from sklearn.preprocessing import StandardScaler
          scaler = StandardScaler()
          X = scaler.fit_transform(X)
          X_train = scaler.fit_transform(X_train)
          X_test = scaler.transform(X_test)
In [82]: X_train
Out[82]: array([[-1.58438248, 0.1072115, -0.14276339, 0.03334576],
                  [-1.08829139, -2.53123321, 2.67783284, -0.35092979],
[1.13672843, -0.15348755, -0.16820608, 0.86368769],
                  [-1.6900361, 0.72314447, -0.19588896, -2.05114485],
                                 0.02698182, 0.1851622, 0.52080477],
                  [ 0.57766241,
                  [-0.9644631, 0.30908695, -0.49734797, -0.03521515]])
In [83]: | y_train.head()
Out[83]: 1226
                   1
          1085
                   1
          148
                   0
          1178
                  1
          478
                  0
```

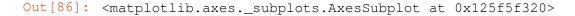
## **Logistic Regression**

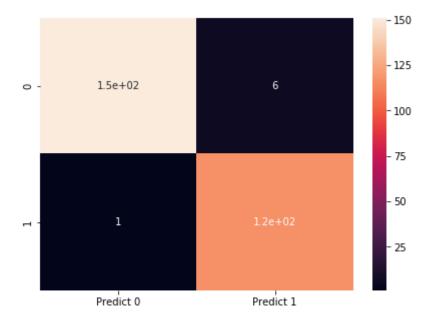
Out[85]: 0.9745454545454545

```
from sklearn.model_selection import cross_val_score
         from sklearn.metrics import accuracy_score
         classifier=LogisticRegression(solver='liblinear', random_state=1)
         classifier.fit(X_train,y_train)
         accuracies=cross_val_score(estimator=classifier, X=X_train, y=y_train, cv=10) # C
         V: Determines the cross-validation splitting strategy (How many folds, default
         is 5-folds) Evaluate a score by cross-validation. estimator: object to use to f
         it the data.
         print ("Accuracies:\n", accuracies)
         y_test_pred=classifier.predict(X_test)
         print("Mean Accuracy: ",accuracies.mean())
         Accuracies:
          [0.98181818 0.99090909 0.98181818 0.99090909 0.99090909 0.99090909
          0.96363636 0.99082569 0.97247706 0.98165138]
         Mean Accuracy: 0.9835863219349459
In [85]: | accuracy_score(y_test,y_test_pred)
```

In [84]: **from sklearn.linear\_model import** LogisticRegression

Confusion Matrix For Logistic Regression

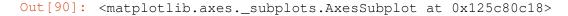


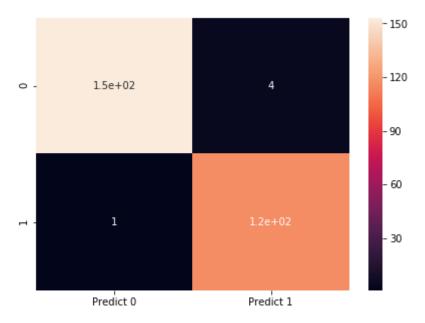


## **Support Vector Machine**

Out[89]: 0.98181818181818

Confusion Matrix For svm\_pred





## **Support Vector Machine (rbf)**

Kernels in SVM classification refer to the function that is responsible for defining the decision boundaries between the classes. Apart from the classic linear kernel which assumes that the different classes are separated by a straight line, a RBF (radial basis function) kernel is used when the boundaries are hypothesized to be curve-shaped.

RBF kernel uses two main parameters, gamma and C that are related to:

- 1. the decision region (how spread the region is), and
- 2. the penalty for misclassifying a data point

0.96296296 1.

Mean Accuracy: 0.9927248677248677

#### respectively

```
In [91]: from sklearn.svm import SVC

svm_rbf_classifier=SVC(kernel='rbf', gamma='auto')
svm_rbf_classifier.fit(X_train, y_train)

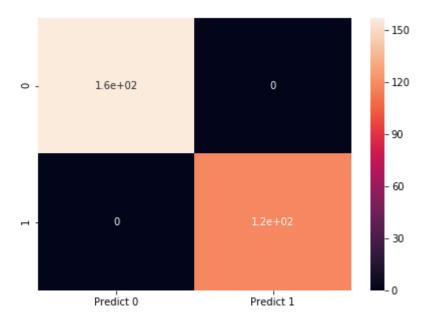
svm_rbf_accuracies=cross_val_score(estimator=svm_rbf_classifier, X=X_test, y=y_test, cv=10)
print("Accuracies:\n", svm_rbf_accuracies)
print("Mean Accuracy: ", svm_rbf_accuracies.mean())

Accuracies:
[1. 0.96428571 1. 1. 1. 1. 1.
```

]

Confusion Matrix For svm\_rbf

## Out[93]: <matplotlib.axes.\_subplots.AxesSubplot at 0x126c31cc0>



```
In [ ]:
```

### RandomForestClassifier

```
In [94]: from sklearn.ensemble import RandomForestClassifier

rdf_classifier=RandomForestClassifier(n_estimators=50,criterion='entropy',random_state=0)

rdf_classifier.fit(X_train,y_train)

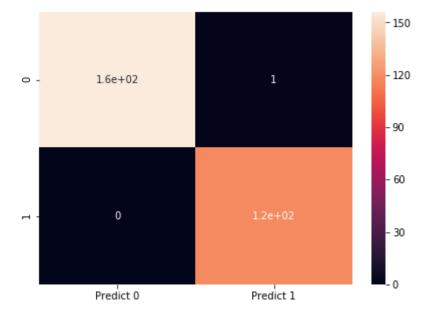
rdf_accuracies=cross_val_score(estimator=rdf_classifier,X=X_test,y=y_test,cv=1
0)

print("Accuracies:\n",rdf_accuracies)
print("Mean Accuracy: ",rdf_accuracies.mean())
```

### Out[95]: 0.9963636363636363

Confusion Matrix For Random Forest

Out[96]: <matplotlib.axes.\_subplots.AxesSubplot at 0x126f4d160>

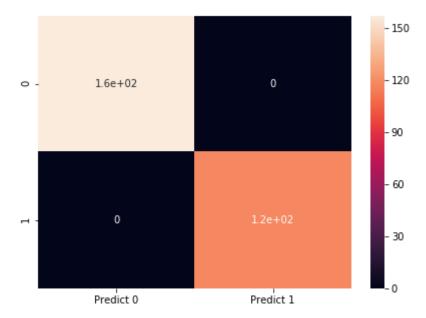


# **KNeighborsClassifier**

```
In [97]:
          from sklearn.neighbors import KNeighborsClassifier
          from sklearn.model_selection import KFold, GridSearchCV
         param_grid = {
              'leaf_size' : [2,5,7,9,11],
              'n_neighbors' : [2,5,7,9,11],
              'p' : [1,2]
          }
          grid = GridSearchCV(KNeighborsClassifier(), param_grid = param_grid)
          grid.fit(X_train, y_train)
Out[97]: GridSearchCV(cv=None, error_score=nan,
                       estimator=KNeighborsClassifier(algorithm='auto', leaf_size=30,
                                                      metric='minkowski',
                                                      metric_params=None, n_jobs=None,
                                                      n_neighbors=5, p=2,
                                                      weights='uniform'),
                       iid='deprecated', n_jobs=None,
                       param_grid={'leaf_size': [2, 5, 7, 9, 11],
                                   'n_neighbors': [2, 5, 7, 9, 11], 'p': [1, 2]},
                       pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                       scoring=None, verbose=0)
In [98]: grid.best_params_
Out[98]: {'leaf_size': 2, 'n_neighbors': 2, 'p': 1}
In [99]: | final_KNN_Model = grid.best_estimator_
In [100]: | KNN = KNeighborsClassifier(n_neighbors=2,p=1,leaf_size=2)
In [101]: | # Call Nearest Neighbour algorithm
          KNN.fit(X_train, y_train)
Out[101]: KNeighborsClassifier(algorithm='auto', leaf_size=2, metric='minkowski',
                               metric_params=None, n_jobs=None, n_neighbors=2, p=1,
                               weights='uniform')
In [102]: KNN_predicted = KNN.predict(X_test)
          accuracy_score(y_test,KNN_predicted)
Out[102]: 1.0
```

Confusion Matrix For KNN

Out[103]: <matplotlib.axes.\_subplots.AxesSubplot at 0x12706aac8>



# **Multilayer Perceptron**

https://scikit-learn.org/stable/modules/generated/sklearn.neural\_network.MLPClassifier.html (https://scikit-learn.org/stable/modules/generated/sklearn.neural\_network.MLPClassifier.html)

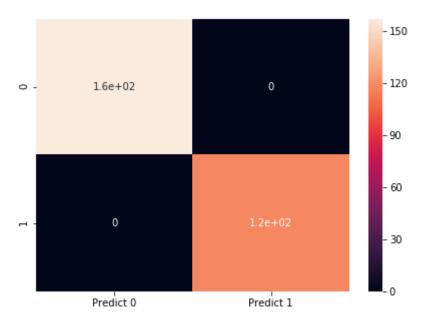
```
Iteration 1, loss = 1.02065261
Iteration 2, loss = 1.00232763
Iteration 3, loss = 0.97715486
Iteration 4, loss = 0.94973488
Iteration 5, loss = 0.92231418
Iteration 6, loss = 0.89651964
Iteration 7, loss = 0.87283524
Iteration 8, loss = 0.85051410
Iteration 9, loss = 0.83056223
Iteration 10, loss = 0.81132826
Iteration 11, loss = 0.79467501
Iteration 12, loss = 0.77862224
Iteration 13, loss = 0.76455037
Iteration 14, loss = 0.75105250
Iteration 15, loss = 0.73882781
Iteration 16, loss = 0.72727541
Iteration 17, loss = 0.71657090
Iteration 18, loss = 0.70615519
Iteration 19, loss = 0.69650376
Iteration 20, loss = 0.68705241
Iteration 21, loss = 0.67795411
Iteration 22, loss = 0.66915932
Iteration 23, loss = 0.66056959
Iteration 24, loss = 0.65225336
Iteration 25, loss = 0.64391579
Iteration 26, loss = 0.63595619
Iteration 27, loss = 0.62803230
Iteration 28, loss = 0.62041858
Iteration 29, loss = 0.61270498
Iteration 30, loss = 0.60516212
Iteration 31, loss = 0.59779594
Iteration 32, loss = 0.59035692
Iteration 33, loss = 0.58320321
Iteration 34, loss = 0.57595144
Iteration 35, loss = 0.56900180
Iteration 36, loss = 0.56205103
Iteration 37, loss = 0.55529365
Iteration 38, loss = 0.54845094
Iteration 39, loss = 0.54178612
Iteration 7939, loss = 0.00267872
Iteration 7940, loss = 0.00267823
Iteration 7941, loss = 0.00267822
Iteration 7942, loss = 0.00267728
Iteration 7943, loss = 0.00267686
Iteration 7944, loss = 0.00267644
Iteration 7945, loss = 0.00267593
Iteration 7946, loss = 0.00267553
Iteration 7947, loss = 0.00267498
Iteration 7948, loss = 0.00267469
Iteration 7949, loss = 0.00267420
Iteration 7950, loss = 0.00267370
Iteration 7951, loss = 0.00267321
Iteration 7952, loss = 0.00267275
Iteration 7953, loss = 0.00267233
Iteration 7954, loss = 0.00267206
Iteration 7955, loss = 0.00267141
Iteration 7956, loss = 0.00267096
Iteration 7957, loss = 0.00267046
Iteration 7958, loss = 0.00267001
Iteration 7959, loss = 0.00266954
Iteration 7960, loss = 0.00266905
Iteration 7961, loss = 0.00266854
Iteration 7962, loss = 0.00266827
Iteration 7963, loss = 0.00266759
```

Iteration 7964, loss = 0.00266713

```
Iteration 7965, loss = 0.00266703
          Iteration 7966, loss = 0.00266623
          Iteration 7967, loss = 0.00266566
          Iteration 7968, loss = 0.00266522
          Iteration 7969, loss = 0.00266476
          Iteration 7970, loss = 0.00266438
          Iteration 7971, loss = 0.00266380
          Iteration 7972, loss = 0.00266325
          Iteration 7973, loss = 0.00266272
          Iteration 7974, loss = 0.00266232
          Iteration 7975, loss = 0.00266184
          Iteration 7976, loss = 0.00266140
          Iteration 7977, loss = 0.00266092
          Iteration 7978, loss = 0.00266053
          Iteration 7979, loss = 0.00266003
          Iteration 7980, loss = 0.00265940
          Iteration 7981, loss = 0.00265899
          Iteration 7982, loss = 0.00265848
          Iteration 7983, loss = 0.00265816
          Iteration 7984, loss = 0.00265794
          Iteration 7985, loss = 0.00265720
          Iteration 7986, loss = 0.00265674
          Iteration 7987, loss = 0.00265626
          Iteration 7988, loss = 0.00265585
          Iteration 7989, loss = 0.00265543
          Iteration 7990, loss = 0.00265495
          Iteration 7991, loss = 0.00265449
          Iteration 7992, loss = 0.00265408
          Iteration 7993, loss = 0.00265365
          Iteration 7994, loss = 0.00265305
          Iteration 7995, loss = 0.00265277
          Iteration 7996, loss = 0.00265212
          Iteration 7997, loss = 0.00265191
          Iteration 7998, loss = 0.00265126
          Iteration 7999, loss = 0.00265093
          Iteration 8000, loss = 0.00265054
In [105]: | print("Accuracies:\n", multi_accuracies)
          print("Mean Accuracy: ", multi_accuracies.mean())
          Accuracies:
           [1.
                       1.
                                  1.
                                             1.
                                                         1.
                                                                    1.
           0.92592593 1.
                                 1.
                                             1.
                                                       ]
          Mean Accuracy: 0.9925925925925926
In [106]: | multi_predicted = multi_classifier.predict(X_test)
In [107]: | accuracy_score(y_test, multi_predicted)
Out[107]: 1.0
```

Confusion Matrix For MLPClassifier

Out[108]: <matplotlib.axes.\_subplots.AxesSubplot at 0x12718aa20>



```
In [ ]:
```

## **Printing each Algorithm and the accuracy score**

It can be seen that Support Vector Machine (using kernel=rbf), KNeighborsClassifier: 1.0 and MLPClassifier: 1.0 are having hightest accuracy score of 100% and RandomForestClassifier is also doing very great with accuracy score of 99%

These can also be verified from the confusion matrix

MLPClassifier: 1.0

Accuracy of 100% is quite weired and I suggest you try different approach to verify this such instead of 80:20, try 70:30 splitting and also try tuning the parameters of the different algorithms to verify you results

logistic regression documentation: <a href="https://scikit-learn.org/stable/modules/generated/sklearn.linear\_model.LogisticRegression.html">https://scikit-learn.org/stable/modules/generated/sklearn.linear\_model.LogisticRegression.html</a>) (https://scikit-learn.org/stable/modules/generated/sklearn.linear\_model.LogisticRegression.html)

SVM documentation: <a href="https://scikit-learn.org/stable/modules/svm.html">https://scikit-learn.org/stable/modules/svm.html</a> (https://scikit-learn.org/stable/modules/svm.html)

GridSearchCV: <a href="https://scikit-learn.org/stable/modules/generated/sklearn.model\_selection.GridSearchCV.html">https://scikit-learn.org/stable/modules/generated/sklearn.model\_selection.GridSearchCV.html</a> (<a href="https://scikit-learn.org/stable/modules/generated/sklearn.model\_selection.GridSearchCV.html">https://scikit-learn.org/stable/modules/generated/sklearn.model\_selection.GridSearchCV.html</a>)

In [ ]:	
In [ ]:	